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Risk Preference Dynamics around Life Events

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NON-TECHNICAL SUMMARY

Risk preferences are an important component of human decision making. A person's willingness to take risks, such as purchasing risky assets, starting a business or breaking the law, can greatly determine the lifetime economic and social trajectory of that person. An important question is whether risk preferences are stable over the life-course and whether any instability is deterministic (i.e. driven by observable changes in the person or her environment) or simply measurement error. Related to this is the question of whether changes in risk preferences are transient or permanent. This matters for policy makers because it provides information on whether policy changes could have indirect effects on risk preferences, how long these effects might last, as well as whether preferences are malleable and could be shaped to meet desirable social objectives.

I make two main contributions to the literature. First, I study whether risk preferences change in response to common life events (changes in finances, health shocks, parenthood, property crime and bereavement) and whether there are important dynamics in the response function. More specifically, I explore whether the response to risk preferences is stronger closer to the event date and decreases over time. Second, I test for mechanisms between life events and risk preferences (i.e. why do risk preferences change in response to life events?).

The data for my study are from the Household, Income and Labour Dynamics in Australia survey. The main risk preference instrument I use is stated willingness to take financial risks. My estimation strategy controls for the fact that those who experience life events may be innately more/less risk averse. I find that risk preferences do respond to certain life events. People tend to be more willing to take risks after an improvement in finances and are more risk averse after a worsening in finances, birth of first child or death of a child or spouse. Importantly, these effects are more pronounced closer to the event date and tend to disappear over time, supporting a model of preference stability in which variation over time is at least partially deterministic but preferences are mean reverting. The mechanisms underlying these risk preference dynamics are explored. I find limited support for the hypotheses that changes in total expenditure, mental health or mood explain the results. Instead, emotional stability is found to be an important moderator – responses to life events are generally stronger for those with low emotional stability – implying that emotions play an important role.

ABOUT THE AUTHORS

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ABSTRACT

Using a panel of Australians I estimate the dynamic relationship between common life events and risk preferences. Changes in financial circumstances, parenthood and family loss predict changes in risk preferences. Importantly the effects are largest closer to the event date and disappear over time. This supports a model of preference formation where risk preferences are (trend) stable but fluctuations are at least partly deterministic. The linkages between life events and risk preferences are explored. There is little evidence that changes in consumption, state dependence, or changes in mental health and mood explain the results. However, emotional stability is an influential moderator suggesting that emotions play an important role.

Keywords: risk preferences; life events; dynamics; fixed effects ordered logit; Australia

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1 Introduction

Risk preferences are a key determinant of economic behavior. Traditionally, economists have treated these preferences as stable across time and state-space (Stigler & Becker, 1977). However, there is considerable controversy around this assumption. Twin studies suggest that the genetic component in risk preferences is relatively low – between 15-35% (Cesarini et al., 2009; Le et al., 2010; Benjamin et al., 2012). Considerable within-variation in risk preferences is frequently found in datasets that track individuals across time (Chuang & Schechter, 2015; Mata et al., 2018). Some researchers have suggested that underlying preferences are relatively stable and that variation over the life course is largely noise (e.g. Sahm, 2012; Salamanca, 2016). On the other hand, evidence of a deterministic component comes from research that links shifts in risk preferences to significant natural events such as hurricanes, floods, earthquakes and tsunamis (Eckel et al., 2009; Page et al., 2014; Cameron & Shah, 2015; Said et al., 2015; Cassar et al., 2017; Hanaoka et al., 2018) as well as more frequent life experiences such as health shocks (Decker & Schmidtz, 2016), exposure to violent crime and conflict (Voors et al., 2012; Brown et al., 2017), parenthood (Görlitz & Tamm, 2015; Browne et al., 2016) and changes in financial circumstances (Anderson et al., 2008). People also appear to become more risk averse as they get older (e.g. Schurer, 2015; Mata et al., 2016; Dohmen et al., 2017).

In addition to understanding whether risk preferences change over time, it is also important to understand *why* they change. In the expected utility paradigm, changes in risk preferences over time can be explained by fluctuations in consumption if the curvature of the utility function depends on consumption. On the other hand, risk preferences might change due to state-dependence if the parameters of the utility function themselves depend on current circumstances (Anderson et al., 2008). It is also possible that variation in risk preferences is explained by human traits not easily incorporated in expected utility theory, such as mental health and emotions. These explanations, which are not mutually exclusive, imply fundamentally different things about the nature of the decision function.

The goal of this paper is to explore the role of common personal life events in explaining short-run dynamics in risk preferences and to explore mechanisms behind any changes in preferences. Specifically, I focus on changes in financial circumstances, injury or illness, parenthood, family loss and crime victimisation. These events are particularly important since most people will experience one or more throughout their lifetime.

There are two main contributions of this research. The first is to focus on dynamics in risk preferences around life events and study both anticipation and adaptation effects.[1] If the mechanisms that link life events to risk preferences, for example consumption shocks or emotional states, are only temporarily affected, then we should expect the same pattern in risk preferences. This would be consistent with risk preferences being a stationary time series process in which individuals have a (trend) stable underlying preference that is quickly mean reverting (e.g. Schildberg-Hörisch, 2018). Failure to account for this structure could hide important relationships between life events and preferences with significant policy implications. For example, if life-shocks cause only temporary deviations in risk preferences then efforts to manipulate preferences may be undermined by this. On the other hand, if policy makers are concerned about the lasting effect of policies on risk preferences, then a pattern of mean reversion may be reassuring.

The second major contribution is to test for mechanisms linking life events to changes in risk preferences. There is little understanding about the channels between life events and risk preferences, yet this information is critical if we are to predict when life events will matter, who are most vulnerable and whether and how the effect of life events can be managed. I test for changes in consumption, changes in the marginal utility of consumption and changes in emotions as potential channels.

I also make other important advances. By utilizing several years of panel data, I am able to control for unobserved time invariant heterogeneity. Most of the literature on risk

[1] Decker and Schmidtz (2016) do not test for anticipation effects but do estimate the effect of health shocks on risk preferences up to four years after the event. Görlitz and Tamm (2015) test for anticipation and adaptation effects but only consider parenthood.

preferences and life events to date has used cross sectional data or has not exploited within temporal variation. I am also able to estimate the effect of multiple life events in a single econometric model. This is important since certain shocks, such as adverse health shocks and changes in finances, are likely to be correlated. It is also valuable to derive estimates within a unified dataset – to date results on different types of life events typically relate to different samples, contexts and methodologies, making them difficult to compare.

The existing empirical literature on the stability of risk preferences around life events is characterized by considerable heterogeneity in terms of preference measures, definitions of life events, study populations and statistical methodologies. Unsurprisingly, there is also heterogeneity in the findings from these studies. In Table A1 I summarize studies in which some measure of risk preferences is the outcome variable and one or more of the life events considered in this paper is a control. One important finding from this review is that very few studies deal with either the endogeneity of life events or the dynamic relationship between life events and risk preferences; both are addressed in this paper.

Studies tend to find that changes in wealth and income are either uncorrelated with risk preferences (e.g. Sahm, 2012; Dohmen et al., 2016) or that favorable financial shocks increase willingness to take risks (Anderson et al., 2008; Paravisini et al., 2018). Indicators of financial circumstances vary considerably across this literature with studies focusing on general income and wealth (Sahm, 2012; Dohmen et al., 2016), housing wealth shocks (Paravisini et al., 2018) and self-assessed circumstances (Anderson et al., 2008). In contrast to most studies looking at other life events, those looking at finances have typically used panel data to at least partially control for innate preferences, although only one study (Paravisini et al., 2018) explicitly controls for individual fixed effects . There has also been a wide range of preference measures including stated preferences (Dohmen et al., 2016), behaviorally elicited preferences (Anderson et al., 2008), preferences from revealed choice (Paravisini et al., 2018) and preferences from hypothetical choices (Sahm, 2012).

Although several studies estimate the effect of various health shocks on risk preferences

(Sahm, 2012; Chuang & Schechter, 2015; Gloede et al., 2015; Decker & Schmidtz, 2016; Dohmen et al., 2016), only Decker and Schmidtz (2016) find a consistent statistically significant relationship between health shocks and risk preferences, with deteriorating grip strength associated with increased risk aversion. Although all these studies use panel data, none control for individual fixed effects. Only a few studies have looked at parenthood; however, the evidence there is more consistent. Wang et al. (2009), Görlitz and Tamm (2015) and Browne et al. (2016) all find a positive association between parenthood and risk aversion. Görlitz and Tamm (2015) is closest to the current study, since they explore dynamics around the birth, finding that the impact of parenthood fades over time. The measure of crime used in this paper is being the victim of property crime. The focus on property crime is important since this form of crime is relatively frequent, and while less severe than other forms of crime, could potentially influence the risk preferences of a large proportion of the population. I am not aware of any study in a developed country context that focuses on a similar measure of crime.[2] There is also little evidence around bereavement. Two studies find no statistically significant relationship for the death of a spouse (Browne et al., 2016; Salamanca, 2016) although neither allows for the possibility of dynamics in the response function.

With few exceptions (Anderson et al., 2008; Paravisini et al., 2018), studies estimating the effects of life events on risk preferences have used either stated preferences or responses to hypothetical scenarios. This is unsurprising since there is generally no or limited time series data for laboratory or field experiment samples and these samples are typically constrained by limited observations. Important to the use of stated preferences, Dohmen et al. (2011) have undertaken an extensive validation of these measures against behavioral benchmarks. I follow the existing literature in using stated risk preferences. I test the validity of my risk preference measure by demonstrating i) that it correlates with personal characteristics in expected ways and ii) it strongly predicts actual risk-taking behaviors.

[2] Chuang and Schechter (2015) regress risk aversion on the change in the value of items stolen for a sample of rural Paraguayans and find a positive correlation between theft and risk willingness in one period but no statistically significant effect in a subsequent period.

Why is the evidence on risk preferences and life events so mixed? One concern is that many existing studies may suffer from endogeneity. Individuals who are more likely to experience particular life events are also likely to differ systematically from other individuals in ways that may be related to their risk preferences. I address this issue by using panel data to control for individual fixed effects. I also allow for the possibility that differences in risk preferences emerge before the event by estimating anticipation effects. This could be important if life events are brought about by other shocks that themselves shift risk preferences. It is also possible that life events do affect risk preferences but the effect is only temporary and therefore missed in models that do not account for this. I allow for this possibility by modelling dynamics.

To estimate the effect of life events on risk preferences I use data from a large Australian household panel survey. These data are particularly advantageous as I can estimate effects in quarters since the event, allowing me to explore the possibility of very short-run adaptation. After sample restrictions I am able to track the life events of almost 5,000 individuals between 2004–2016. I find that risk preferences do respond to certain life events. Improvements in finances are found to increase risk willingness while worsening finances, parenthood and the death of a spouse or child are associated with increased risk aversion. On the other hand, health shocks and property crime do not affect preferences. Importantly, the impact of any life event tends to be more pronounced closer to the event date and disappears over time. This is consistent with a model of preference formation in which preferences are mean reverting but fluctuations over time are at least partly deterministic. The results have important implications for understanding how preferences evolve over the life course, when preferences are likely to change, the malleability of preferences in adulthood and the external validity of preferences elicited in different contexts.

In exploring the pathways between life events and risk preferences, I find only weak evidence that changes in consumption (i.e. a direct relationship between consumption and risk preferences, such as with decreasing absolute risk aversion (DARA) utility) explains the results and this is only for the change in financial circumstances life events. There is also little evidence that state-dependence – as reflected by changes in the marginal utility of consumption – or changes in mental health or mood are important. Instead, the influence of life events on risk preferences is found to be moderated by emotional stability, implying a key role for emotional regulation.

The paper is organized as follows. In Section 2 I discuss the theoretical linkages between life events and risk preferences. In Section 3 I discuss the data. In Section 4 I discuss the estimation strategy. In Section 5 I present the main results. Section 6 concludes.

2 Conceptual framework

To begin I present a simple conceptual framework for thinking about the relationship between life events and risk preferences. In order to embed common utility functions, such as constant absolute risk aversion (CARA) and DARA, I consider an agent with a more general hyperbolic absolute risk aversion (HARA) utility function. Using the notation of Merton (1971), the agent derives utility U from consumption C according to

$$U(C) = \frac{1-\gamma}{\gamma}\left(\frac{\beta C}{1-\gamma} + \eta\right)^{\gamma}. \tag{1}$$

subject to the restrictions that $\gamma \neq 1$, $\beta > 0$, $\frac{\beta C}{1-\gamma} + \eta > 0$ and $\eta = 1$ if $\gamma = -\infty$. The coefficient of absolute risk aversion $A(C) = -U''(C)/U'(C)$ is a function of consumption and the parameters of the HARA utility function γ, β and η.

$$A(C) = \frac{1}{\frac{C}{1-\gamma} + \frac{\eta}{\beta}} \tag{2}$$

It is straightforward to show that $A(C)$ is decreasing for the range $-\infty < \gamma < 1$ (DARA utility function) and approaches a constant as γ approaches $+\infty$ (CARA utility function). The case of increasing absolute risk aversion is also possible if $1 < \gamma < +\infty$; however this is an uncommon specification in practice.

In equation (1) the parameters of the utility function, other than C, are treated as exogenous and stable across time and context. As an extension to the basic specification, consider the case where γ depends on the current state of the world $\theta \in \Theta$ so that $\gamma = \gamma(\theta)$. Different states of the world could include for example a good health state, a poor health state, a state in which the person is stressed, sad or fearful and so on. Importantly, states may be temporary and the relationship between θ and γ may be time dependent. This gives rise to the possibility that risk preferences depend not only on experiencing various states of the world, but are also a function of how long ago this occurred.

Applying this framework to the current project, it is clear that life events can influence risk preferences through two broad channels. First, life events may affect risk preferences through their effect on consumption. Most of the life events considered in this study could reasonably be expected to decrease consumption, which may increase risk aversion if people have DARA preferences ($A'(C) < 0$) or leave risk aversion unaffected if they have CARA preferences ($A'(C) = 0$). It is also worth noting that according to prospect theory (Kahneman & Tversky, 1979) people are more willing to take risks after a loss, giving rise to the possibility that risk aversion decreases after an adverse wealth shock.

The second channel is state dependence in which the parameters of the utility function (e.g. γ) depend on the current state of the world θ. One possibility is that certain events lower the experienced utility of consumption (i.e. increase γ). For example, Finkelstein et al. (2013) provide evidence that marginal utility of consumption decreases in worse health states. Life events might also place individuals in different emotional states. Worsening finances, worsening health and being the victim of property crime, are likely to elevate fear, which has been shown to increase risk aversion (Lerner & Keltner, 2001; Cohn et al., 2015; Guiso et al., 2017). Stress is also likely to be elevated by negative life events and has been linked to changes in risk preferences, although the evidence is mixed, with some studies finding that stress increases risk aversion (Porcelli & Delgado, 2009; Kandasamy et al., 2014;

Cahlíková & Cingl, 2017), while others find it increases risk willingness (Starcke et al., 2008; Putman et al., 2010; Pabst, Brand, & Wolf, 2013; Pabst, Schoofs, et al., 2013) or has no significant effect (Delany et al., 2014; Sokol-Hessner et al., 2016). Sadness has also been linked to both increased risk aversion (Campos-Vasquez & Cuilty, 2014) as well as increased risk willingness (Raghunathan & Pham, 1999). Raghunathan and Pham (1999) suggest that sadness may increase risk taking as people seek reward replacement. Mental health may also be affected by life events and adverse states have been associated with more conservative investment behavior (Bogan & Fertig, 2013; Lindeboom & Melnychuk, 2015). A different line of argument comes from evolutionary adaptation. For example, from an evolutionary perspective there is cause for new parents to become more risk averse, since actions risking survival are more costly when death leaves children vulnerable (Wang et al., 2009).

While the theoretical framework motivates studying the relationship between risk preferences and life events, it is unable to provide strong predictions for the direction of such relationships. Nevertheless, it does provide important insights into modelling this relationship. To the extent that life events constitute only temporary deviations in the state of the world or consumption, this may in turn give rise to only temporary fluctuations in risk preferences. In some cases life events may only exert a short-term influence, such as monetary windfall gains and losses or transient health shocks. Even for events that are long-lasting or permanent, such as parenthood, the effect on risk preferences may be more pronounced closer to the event date if the underlying mechanisms, for example changes in mood, mental health or biological triggers, are themselves only temporarily affected. This suggests modelling dynamics around life events.

3 Data

3.1 Overview

The data for this study are from the Household Income and Labour Dynamics in Australia (HILDA) Survey, a large panel dataset that commenced in 2001 with a random population sample of 7,682 households (13,969 individuals aged 15 years and older completed the survey in wave 1). Participants have been tracked every year since. At the time of writing there are 16 waves (2001-2016) of data available.

The main risk preference question used in this study was asked in 2006, 2008 and then every year from 2010.[3] To avoid measurement error in the entire vector of life event-year combinations, it is helpful to restrict the sample to a balanced panel of individuals. The sample used to construct covariates comprises a balanced panel of individuals responding in every year between 2004-2016[4]. The sample is also restricted to those 18 years or older in 2004.

The resulting estimation sample consists of 4,810 individuals and $T = 8$ years in which risk preferences are observed (2006, 2008 and 2010-2015). Note that 2016 is not included in the estimation sample so that anticipation effects can be estimated for up to one year. To better understand the population under study, descriptive statistics for 2006 and 2014 are presented for key demographic variables in Table 1 (information on wealth is available in these years). In 2006, the mean age is 47.5 years and real household disposable income is $AUD80,856 per year (2011 dollars). 46% of the sample are male. The sample means for most time varying variables are relatively stable between 2006 and 2014. The main changes are in income and employment, with mean income increasing by just over $AUD9,000 on

[3]The question was asked in some earlier waves but has only partial coverage because people could opt-out of answering if they indicated they did not have discretionary income for investing.

[4]Note that this means that in year 1 of the estimation (2006) I can control for if a life event occurred 2-3 years ago but do not control for life events that occurred earlier than this. Since the results generally indicate substantial adaptation to life events by this point, this is a reasonable trade-off point between comprehensively controlling for the life event history and reducing the sample size by moving the base period further back. To the extent that life events that occurred prior to this window resulted in a permanent shift in risk preferences, this will be captured by individual fixed effects.

average, employment decreasing from 69% to 61% and retirement increasing from 19% to 31%. There is considerable representation of different groups in terms of education level, migrant status, employment, geographic location and couple status.

Table 1: Descriptive statistics

		Mean	
Variable	Description	2006	2014
Age	Age in years	47.50	55.50
		(14.08)	(14.08)
Male	=1 if male	0.459	0.459
Disposable income	Household disposable income ($AUD 2011)	$80,856	$89,899
		(56,893)	(69,330)
Overseas	=1 if born overseas	0.216	0.216
University	=1 if highest academic achievement degree	0.269	0.290
Diploma	=1 if highest academic achievement diploma	0.110	0.119
Mother secondary	=1 if mother completed secondary education	0.295	0.295
Father secondary	=1 if father completed secondary education	0.496	0.496
Student	=1 if currently full-time student	0.024	0.008
Rec. dividends	=1 if receives income from dividends	0.327	0.289
Total assets	Total value of household assets ($AUD 2011)	$1,055,036	$1,181,185
		(1,533,988)	(1,400,369)
Home owner	=1 if home owner	0.778	0.817
Own property	=1 if own property in addition to home	0.219	0.236
Equity ratio	Ratio of equities to total assets	0.045	0.033
Self-employed	=1 if self-employed	0.078	0.066
Region	=1 if lives outside major city	0.124	0.124
Employed	=1 if employed	0.689	0.606
Unemployed	=1 if unemployed	0.018	0.014
Retired	=1 if retired	0.193	0.312
Couple	=1 if coupled (married or defacto)	0.747	0.746

Note: There are 4,810 individuals in each year. Values for household income and assets include imputed values for missing information, which are supplied with the HILDA survey data. Household disposable income is a derived variable based on gross income net of the expected tax liability, which takes into account personal and family circumstances. Further details are in the HILDA User Manual (Summerfield et al., 2017). Standard deviations for continuous variables are in parentheses.

3.2 Outcome variables

The main outcome variable in this paper is a measure of self-assessed risk preferences in the financial domain. This question is based on a regular survey item contained in the U.S.

Survey of Consumer Finance and has been used in previous studies to estimate the effect of the Great Depression and the Global Financial Crisis on investor risk preferences (Malmedier & Nagel, 2011; Guiso et al., 2017). Participants are asked the following question.

> Which of the following statements comes closest to describing the amount of financial risk that you are willing to take with your spare cash? That is, cash used for savings or investment.

Participants can choose from the following responses (emphasis not added).

1. I take <u>substantial</u> financial risks expecting to earn substantial returns
2. I take <u>above-average</u> financial risks expecting to earn above-average returns
3. I take <u>average</u> financial risks expecting to earn average returns
4. I am not willing to take <u>any</u> financial risks
5. I never have any spare cash

In the waves used in this study, people who choose option 5 are given the following follow-up question.

> Assume you had some spare cash that could be used for savings or investment. Which of the following statements comes closest to describing the amount of financial risk that you would be willing to take with this money?

They are then asked to choose from 1-4 above.

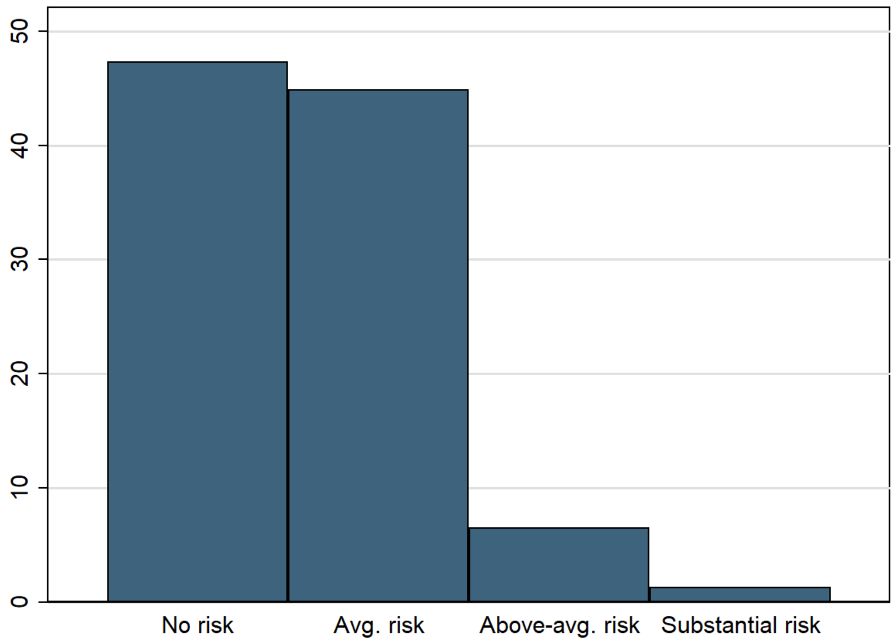
I pool responses from people who answer in respect of hypothetical money (i.e. those choosing option 5 above) and those who answer in respect of real money. 12.5% of the risk preference values in my data are elicited with respect to hypothetical money.[5]

The distribution of pooled responses to the risk elicitation question are presented in Figure 1. Most people seem to be risk averse in the sense that they are either not willing to

[5] In Appendix C (Table C1) I present the main results with observations relating to hypothetical responses dropped from the estimation. The results are not sensitive to including hypothetical responses.

take any financial risks or are only willing to take average risks. Around 8% of people are willing to take above-average or substantial risks.

Figure 1: Distribution of risk preferences in financial domain



Note: Results are for the pooled sample of 4,810 individuals across eight years 2006, 2008 and 2010-2015 (38,480 observations).

The key question is whether the HILDA instrument is a valid measure of risk preferences. One attractive feature of the question is that it speaks directly to behaviors of individuals by asking what they would do with spare cash available for investment. On the other hand, there is little guidance on what different levels of risk taking actually mean and there is no financial incentive for participants to reveal their true preferences. The former issue is potentially dealt with by controlling for individual fixed effects, since different interpretations of risk categories should show up as individual specific unobserved heterogeneity. On the relative value of survey measures of risk preferences versus behavioral measures, Dohmen et al. (2011) have found that questions on general and domain specific risk attitudes are highly correlated with incentivized monetary tasks typically used in experimental work. Frey et al. (2017) evaluated 39 different risk elicitation instruments – including common behavioral tasks with monetary stakes as well different attitudinal questions – and found that the attitudinal measures were better able to capture an underlying common risk preference, performed markedly better in test-retest analysis, and therefore may be a more reliable measure of underlying risk-taking behavior.

More formally, if the HILDA question is a valid measure of risk preferences, then we should be able to predict its correlation with known correlates of risk preferences from previous research. It should also be able to predict risky investment behavior, such as owning shares. To test this, I first follow Dohmen et al. (2011) and examine the correlation between the survey measure and four plausibly exogenous variables that have been found to correlate with risk willingness in previous studies: age (-); being male (+); height (+); and parental education (+). The results from a linear OLS regression are reported in column 2 of Table 2.[6] Note that the risk preference levels have been rescaled so that 1 corresponds to not being willing to take any risks and 4 corresponds to being willing to take substantial risks (and then standardized). All variables show the expected correlations and are individually and jointly highly significant. Next I include two additional variables that frequently predict a higher propensity to take risks but are unlikely to be exogenous, namely (log) household income and an indicator for having obtained a university degree. Again, the correlations are in the expected direction and, apart from age, remain statistically significant.

It is worth highlighting that the risk preference question is strongly framed in the financial domain. In other studies using attitudinal proxies for risk preferences, the elicitation question is often asked in the general domain e.g. how willing are you to take risks in general? Questions framed in specific domains have been shown to better predict behavior relevant to that domain (Weber et al., 2002; Dohmen et al., 2011). In the present context, this means that the risk preference question is likely to be a better predictor of financial risk taking than a more general instrument. Since financial decision making is of significant importance in terms of understanding investment decisions, occupation choices, borrowing decisions and so on, this is a particularly interesting domain to focus on. Further, the instrument is easier to

[6] Results from ordered logit regression are similar.

Table 2: Correlation risk preferences with key demographics

	Financial domain		General domain	
Age	-0.006***	-0.001	-0.014***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.253***	0.265***	0.352***	0.361***
	(0.030)	(0.028)	(0.040)	(0.040)
Height	0.011***	0.008***	0.005**	0.004
	(0.002)	(0.001)	(0.002)	(0.002)
Mother secondary	0.173***	0.092***	0.128***	0.078**
	(0.026)	(0.025)	(0.032)	(0.032)
Father secondary	0.087***	0.039*	0.057**	0.027
	(0.023)	(0.021)	(0.029)	(0.029)
Ln(Dis. income)		0.255***		0.103***
		(0.014)		(0.021)
University		0.336***		0.217***
		(0.025)		(0.032)
Constant	-1.466***	-4.124***	-0.193	-1.293***
	(0.230)	(0.259)	(0.339)	(0.412)
Observations	38480	38380	4794	4784
R^2	0.066	0.128	0.094	0.111

Note: Risk preferences in the financial domain are measured on a 1-4 scale and are elicited in the years 2006, 2008 and 2010-2015. Risk preferences in the general domain are measured on a 0-10 scale and are elicited in 2014 only. For both measures, higher values correspond to greater willingness to take risks. The coefficients are obtained by linear OLS regression on the standardized values of the different risk preference instruments. The sample size slightly decreases in models that control for household income because those with negative values are dropped from the sample. Cluster robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

interpret than a more general question because it is clearer what type of risk taking behavior the respondent has in mind when answering the question.

Nevertheless, in order to align the outcome measure with other studies and assess the sensitivity of results to the domain, it would be interesting to compare results with a general measure of risk attitudes. In the HILDA survey, general preferences for risk were elicited in a single wave in 2014 using a similar question to the German Socio-Economic Panel (SOEP). Participants were asked the following.

Are you generally a person who is willing to take risks or are you unwilling to

> take risks? Please indicate by crossing one box below. The more willing you are to take risks the higher the number of the box you should cross. The less willing you are to take risks, the lower the number of the box you should cross.

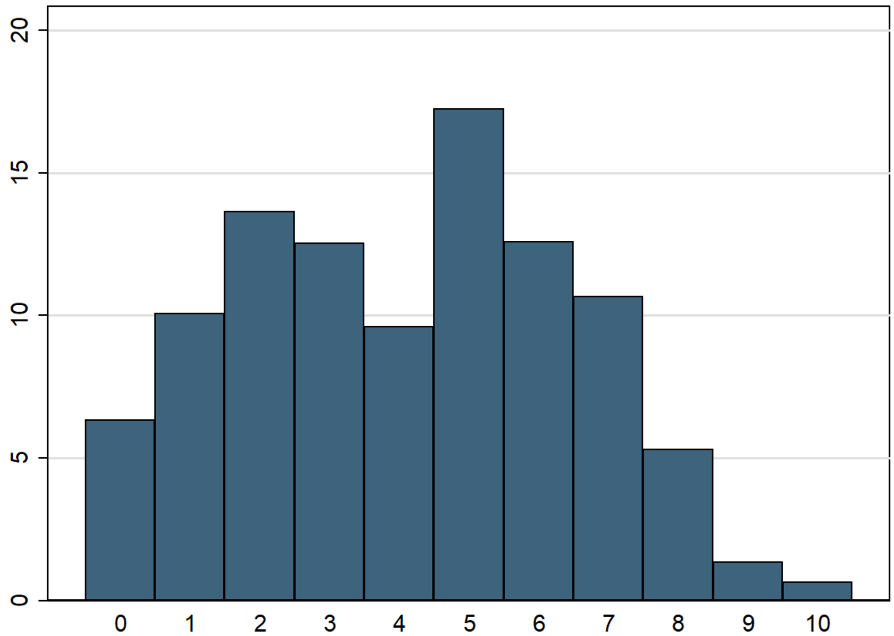
Respondents were then able to cross one box ranked 0-10.

Since preferences in the general domain are only collected in a single wave, I cannot 'transform out' the individual specific unobserved heterogeneity. It also means that I have considerably less variation in life events to identify dynamic anticipation and adaptation effects. Consequently, I only use this measure in sensitivity analysis presented later. When using this variable, I propose a solution to the problem of unobserved heterogeneity by assuming a common underlying fixed effect across risk preference instruments.

In column 3 of Table 2, the general domain risk willingness variable is regressed against the covariates mentioned above. All correlations are in the expected direction although the coefficients for height and father's education are not significant when income and own education are controlled for. The distribution of this variable is presented in Figure 2. The modal choice is 5 and the distribution is left skewed, as in the financial domain. Note there is a strong positive correlation in risk preferences across domains. The polychoric correlation between the two measures is 0.51.

As a further check on the validity of the risk preference instruments, I turn to their predictive power. In Table 3 I regress these instruments (standardized values) on important indicators of risk taking behavior: receiving income from dividends; owning a second property; the share of equities as a proportion of household assets; and an indicator for self-employment. All regressions control for the covariates in Table 2. For the main instrument, all correlations are in the expected direction and highly significant. The effect sizes are also economically meaningful. For example, a one standard deviation increase in the risk score is associated with an increased probability of receiving income from dividends by 7.7 percentage points, owning a second property by 5.1 percentage points, increases the probability of owning equities by 8.9 percentage points, the proportion of equities to total

Figure 2: Distribution of risk preferences in general domain



Note: Results are for the sample of 4,794 individuals in the year 2014. 0 corresponds to extreme unwillingness to take risks in general; 10 corresponds to extreme willingness to take risk in general.

assets (conditional on owning equities) by 1.2 percentage points and the probability of self-employment by 1.9 percentage points. For the general risk measure, these correlations are all positive as well, although the correlation for receiving income from dividends is statistically insignificant. Further, the correlations are smaller in economic magnitude, except for self-employment.

Altogether, both instruments seem to contain valuable information about actual risk taking behavior. However, the main instrument is a stronger predictor of financial decision making, as expected. This is an important advantage of this instrument; it is much clearer what type of behavior is captured.

3.3 Life event variables

The life event data in the HILDA survey is obtained through a regular question asking whether event l has occurred in the previous 12 months. An affirmative response therefore

Table 3: Predictive power of risk preference variables

	Financial domain			
	Rec. div.	Own. prop.	Eq. share	Self emp.
	0.077***	0.051***	0.040***	0.019***
	(0.004)	(0.004)	(0.004)	(0.003)
Observations	38380	14393	14393	24744
Pseudo R^2	0.095	0.071	0.473	0.071
	General domain			
	Rec. div.	Own. prop.	Eq. share	Self emp.
	0.004	0.028***	0.008***	0.030***
	(0.007)	(0.006)	(0.003)	(0.006)
Observations	4784	4784	4874	2,908
Pseudo R^2	0.075	0.061	0.389	0.067

Note: Risk preferences in the financial domain are measured on a 1-4 scale and are elicited in the years 2006, 2008 and 2010-2015. Risk preferences in the financial domain are measured on a 0-10 scale and are elicited in 2014 only. For both measures, higher values correspond to greater willingness to take risks. The predictions for Receives dividends, Own property and Self employed are based on binary logit regressions and are the average marginal effect for a one unit increase in the normalized value of the risk preference variable across the estimation sample. The coefficients on Equity share are obtained via Tobit regressions and the estimate reported is the marginal effect on the Tobit index function. Information on property ownership and equities are only available for 2006, 2010 and 2014. Only those employed are included in the regressions on self-employment. All models control for the following: age, gender, height, mother's education, father's education, ln household income and university degree. Those with negative household income are dropped from the sample and imputed values are used for missing income. Robust and cluster robust standard errors are in parentheses. Standard errors for average marginal effects are obtained via the delta method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

indicates that the event occurred up to one year ago. A follow-up question asks whether the event occurred 0-3, 3-6, 6-9 or 9-12 months ago.[7] This is helpful since it allows us to account for the possibility there are significant effects very close to the event date followed by rapid adaptation. Such effects may be missed if the time since the event is aggregated to a longer duration (e.g. one year). The trade-off is that aggregating may increase precision and is less

[7] In 4-19% of cases (depending on the life event), this follow-up question is not answered. Rather than dropping these respondents, I assume the event occurred 3-6 months ago when this is missing, since this means that misclassification will generally only be in the order of one quarter. Further, if life events exert a stronger influence closer to the event date, this will tend to bias estimates towards zero if misclassification is such that more of the missing values come from events that occurred 6-12 months ago, which is plausible given recall issues. In Appendix C (Table C2) I repeat the main estimation with people with missing life event quarters dropped; the results are consistent with the main results. I also present results controlling for 0-1 year since the event (rather than in quarters), which are less influenced by assumptions around the event date (Table C3).

prone to recall issues.

Using the data from 2004-2016, I construct indicators for whether an event will occur in the next twelve months, occurred 0-3, 3-6, 6-9 or 9-12 months ago, 1-2 years ago or 2-3+ years ago.[8] The base group are those who have not experienced the life event and will not experience it within the next 12 months. Note that it is possible for the same individual to experience the same life event more than once over the data period. I do not restrict these experiences and effectively assume that individuals can be simultaneously affected by life events that occurred different lengths of time ago.[9]

Although the HILDA survey collects information on an extensive range of life events, for feasibility reasons I restrict attention to a subset of events that cover a range of interesting domains (i.e. finances, health, family dynamics and crime) and are likely to be experienced by most people during their lifetime. The frequencies for these life events are presented in Table 4. The most common life event is serious personal injury or illness (3,389 occurrences) while the least common event is death of a spouse or child (291 occurrences). While I include the death of a child in this indicator, there are only 26 such deaths for the sample between 2004-2016, so this life event predominately reflects the loss of a spouse.

It is important to note that the indicators for changes in financial circumstances are subjective. There are several advantages to using subjective indicators. First, they are more likely to capture how people feel about their change in circumstances than objective measures, such as changes in income or wealth fluctuations. This is likely to be particularly important if the way people feel about their new circumstance determines whether it influences their risk preferences. Second, subjective assessments avoid the need to make arbitrary judgements about the definition of a life event. For example, how large does an income shock

[8]For each life event, I determine how long it has been since the event at each wave as precisely as possible by using the survey completion dates. In most cases, surveys are completed approximately one year after the previous survey (median 362 days; mean 361 days; s.d. 30 days).

[9]An alternative approach, that has the disadvantage of using less of the data, would be to assume that when a new event occurs there is immediate adaptation from the previous event by only including dummy variables relating to the most recent event (e.g. Frijters et al. (2011) in the context of life events and subjective wellbeing). I repeat the main estimation under this assumption and report the results in Appendix C (Table C4); the results are consistent with the main results.

Table 4: Frequencies for life events

Life event	When event occurred -(0-1) year	0-1 year	1-2 years	2-3+ years
Major improvement finances	1289	1284	1191	6020
Major worsening finances	960	989	945	4384
Serious personal injury or illness	3501	3389	3016	11132
Birth first child	280	317	312	2841
Victim property crime	1074	1178	1095	6647
Death of spouse or child	311	291	245	1302

Note: Pooled sample size is 38,480 (4,810 individuals). Data are from the years 2006, 2008 and 2010-2015. The questions on life events are part of the self-completion questionnaire in the HILDA survey. Respondents are asked "Did any of these happen to you in the past 12 months".

need to be to constitute a life event? Finally, subjective indicators can more holistically capture changes in circumstances. For example, measuring improvements/worsening finances with income data ignores the fact that financial circumstances could change through changes to cost of living, periodic or one-off expenses and so on.

One disadvantage of using subjective indicators is that it is not necessarily clear what the underlying driver is of the life event. Changes in self-assessed financial circumstances could be driven by changes in income, debt, expenses or the economic outlook. The improvement in finances variable has previously been analysed in Au and Johnston (2015), who argue that it can be thought of as an exogenous increase in income of approximately $AUD50,000. This comes from the fact that bequests and lump sum transfers are highly correlated with this life event, which seems to be partly driven by the way the answer is prompted. In the HILDA questionnaire, participants answer whether they experienced a "major improvement in financial situation (e.g., won lottery, received an inheritance)". There is also prompting in the case of worsening finances; participants answer whether they experienced a "major worsening in financial situation (e.g., went bankrupt)".

To better understand these indicators for the current sample, I regress various controls for wealth shocks (e.g. income fluctuations, lump-sum transfers, housing wealth fluctuations, employment) and expense shocks (e.g. sickness/injury, crime, parenthood, bill stress) on the financial improvement/worsening life event indicators. For brevity, these results are presented and discussed in greater detail in Appendix B. The main findings are that: i) improvements in finances is largely predicted by transfers; and ii) worsening finances is strongly predicted by expense shocks. Consequently, these indicators should not be thought of as strictly reciprocal events. In Appendix B I also present results where the life event indicators for financial circumstances are replaced with indicators for whether household income improved/worsened by 30%, 50% or 70% on the previous year (Table B3). These results are consistent with the main results, although somewhat weaker for favorable financial shocks.

4 Empirical model

The basic estimation equation is given by equation (3). Risk preferences are represented by a linear index function for individual i in period t, with $\gamma_{it}^{\rho l}$ indicating that life event $l \in L$ occurred ρ years ago (negative values indicating that event l will occur in the future). x_{it} is a vector of time-varying covariates, α_i is an unobserved individual fixed effect, which is likely to be correlated with ϵ_{it}, a random error term discussed below.

$$y_{it}^{*} = \sum_{l} \sum_{\rho=-(1-0)}^{2-3+} \beta^{\rho l} \gamma_{it}^{\rho l} + x_{it}^{'} \delta + \alpha_i + \epsilon_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{3}$$

Because risk preferences are only measured on a discrete ordinal scale, I do not observe y_{it}^{*} but only y_{it}. For the main risk preference measure, y_{it} takes on four values with $y_{it} = 1$ corresponding to being unwilling to take any financial risks and $y_{it} = 4$ indicating the individual takes substantial risks. Formally

$$y_{it} = k \text{ if } \tau_{ik} < y_{it}^{*} \leq \tau_{ik+1} \qquad k = 1, 2, 3, 4$$

where τ_{ik} are individual specific thresholds and k are the possible values of y_{it}. There are

$K - 1 = 3$ kink points (thresholds above which y_{it} changes value).

Estimation of equation (3) will deliver consistent estimates of the dynamic impact of life events on risk preferences ($\beta^{\rho l}$) provided that the standard conditional expectation assumption holds. That is, conditional on time varying controls (x_{it}) and unobserved time invariant heterogeneity (α_i), the occurrence of life events is uncorrelated with unobserved time varying determinants of risk preferences in ϵ_{it}. Controlling for α_i is important since innate preferences are likely to influence the occurrence of various life events. It can also pick up individual differences in the way people interpret the risk preference scale, which could be influenced by heterogeneous beliefs about financial risks. Any age-trend or macroeconomic sentiment is captured by year dummies included in x_{it}.[10]

Given the discrete, ordinal nature of the dependent variable it is natural to consider models such as ordered logit and probit. However, dealing with individual fixed effects is problematic in these models due to the incidental parameters problem – solutions available for the linear regression case generally do not result in consistent estimates of the parameters of interest. One alternative is to estimate models with random effects; however, this involves invoking strong additional distributional assumptions. Rather than invoking such assumptions I use the 'blow up and cluster' (BUC) fixed effects ordered logistic regression model discussed in Mukherjee et al. (2008) and Baetschmann et al. (2015).

The BUC estimator is based on the well known conditional maximum likelihood (CML) fixed effects logit model of Chamberlain (1980). Both models assume that ϵ_{it} are independent and identically distributed according to a logistic cumulative distribution function. The CML model dichotomizes the ordered outcome variable and estimates the probabilities for the given sequence of choices over T for each individual conditional on the sum of all choices, which is a sufficient statistic for α_i. Importantly, the conditional probabilities do not depend on α_i. Whereas the standard CML estimator only dichotomizes the ordered outcome variable

[10] x_{it} also includes controls for the following: age^2; education (separate indicators for if highest qualification is a university degree or a diploma); indicator for being a full-time student; indicator for living in a rural area; indicators for whether employed, unemployed or retired; and a couple (married or defacto) indicator.

once, the BUC estimator involves all possible dichotomizations and proceeds on the basis that the estimated parameter values are constant across all thresholds k of y_{it}. Like CML, BUC is consistent but is more efficient since it makes greater use of the available data. The BUC estimator is computationally straightforward, with similar efficiency compared to other consistent fixed effects ordered logit models, and has been found to be more robust than more complicated estimators in finite samples (Baetschmann et al., 2015).

An alternative to BUC is to treat the risk preference value as a continuous variable and estimate a standard linear fixed effects model. This has the advantage of not restricting the distribution of the error term but ignores the fact that y_{it} is discrete and is censored left and right. With only four categories, the bias from estimating a linear fixed effects model may be large and as such the BUC estimator is the preferred specification. In practice, results using linear fixed effects are qualitatively similar to BUC and marginal effects from this model are presented for comparison.

5 Results

5.1 Main regression

Odds ratios (ORs) from BUC estimates for equation (3) are reported in Table 5. The results correspond to a single estimated model controlling for all life events interacted with when they occurred.

To better convey the dynamics in risk preferences, marginal effects from a linear fixed effects regression are presented as a series of two-way graphics in Figure 3, with the horizontal axis representing time until/since the event and the vertical axis representing the marginal effect on the risk preference value.[11]

[11]Note that marginal effects for the BUC estimator depend on α_i, which is cancelled out in the conditional probabilities. These can therefore only be obtained by arbitrarily setting α_i. Linear regression results are qualitatively similar to BUC with quantitatively similar ratios between coefficient estimates. Consequently, this is the preferred estimator for obtaining marginal effects.

Table 5: BUC estimation results

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
0-1 year before	0.969	1.242**	1.135**	1.133	0.952	1.110
	(0.084)	(0.127)	(0.066)	(0.206)	(0.091)	(0.230)
0-3 months after	1.238	0.594***	1.034	0.388**	1.113	0.578
	(0.172)	(0.118)	(0.107)	(0.146)	(0.149)	(0.217)
3-6 months after	1.563***	0.902	1.083	0.535*	1.044	1.320
	(0.204)	(0.148)	(0.106)	(0.183)	(0.158)	(0.456)
6-9 months after	1.221	0.926	0.926	1.008	1.501*	0.501
	(0.222)	(0.239)	(0.121)	(0.362)	(0.312)	(0.222)
9-12 months after	1.254	0.909	1.159	0.695	0.929	0.938
	(0.251)	(0.164)	(0.129)	(0.241)	(0.196)	(0.365)
1-2 years after	1.234**	0.969	1.096	0.755	1.047	0.777
	(0.116)	(0.098)	(0.069)	(0.155)	(0.101)	(0.178)
2-3+ years after	1.098	0.703***	1.032	0.759	1.033	1.059
	(0.110)	(0.075)	(0.077)	(0.142)	(0.106)	(0.226)

Note: N= 31,736. T= 2006, 2008, 2010-2015. The estimation sample size is less than $N(4,180) \times T(8) \times K(3)$ because observations where outcomes do not vary over the period drop out of the likelihood function. Exponentiated coefficients (odds ratios) from a single estimation of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. The estimation controls for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results indicate that common life events are related to changes in risk preferences. Those who experience a major improvement in finances in the previous 3-6 months are 1.6 times more likely to be in a higher risk preference category. This effect diminishes over time – after 1-2 years the OR is 1.2 and by 2-3+ years it is 1.1 and no longer statistically significant. This is consistent with the model of adaptation discussed in Section 2. Surprisingly, a major worsening in finances is associated with greater willingness to take risk in the year preceding the event. One possible explanation is that people who experience a worsening in finances include those who in $t = -1$ become more risk loving and then in $t = 0$ experience a significant loss from this behavior. This loss is associated with an increase in risk aversion – the OR decreases from 1.2 to 0.6 0-3 months after the event. As with favorable financial

Figure 3: Marginal effects: OLS fixed effects regression

Note: N= 38,480 (4,810 individuals). T=2006, 2008, 2010-2015. The estimates are marginal effects (with 95% confidence intervals) from an OLS fixed effects regression on risk preferences (standardized) in the financial domain [1-4 scale].

shocks, risk preferences quickly rebound. However, there is also evidence of a persistent negative effect when looking at the estimate for 2-3+ years. Overall, adverse financial shocks are associated with lower willingness to take risks, implying symmetry in the effects between favorable and unfavorable changes in finances. The more volatile dynamics for worsening finances could indicate that those who experience financial losses are inherently less stable in their preferences.

There is little evidence that an adverse health shock affects risk preferences. Interestingly, risk willingness is statistically significantly higher in the year before the health shock, although the effect is economically modest (OR=1.1). In Appendix C I consider alternative definitions of health shocks and find no evidence they shift risk preferences.[12] Being the victim of property crime also does not appear to influence preferences, with only the estimate for 6-9 months marginally significant. Death of a child or spouse is associated with a large increase in risk aversion immediately after the event (OR = 0.6) as well as after 6-9 months (OR=0.5) but neither estimate is statistically significant. Surprisingly, there is a temporary recovery 3-6 months after the event, which may just reflect noise in the data (noting that these are low frequency events). Later I show that the estimated increases in risk aversion following the death of a spouse or child are statistically significant for those with low emotional stability and males.

New parents are 0.4 times as likely to be in a higher risk category immediately after the birth. As with other events, there is evidence of an adaptation effect. People become less risk averse the less recently the birth occurred – following the point estimates, the OR generally becomes closer to one as time since the birth increases.

Instead of focusing on individual events, it is worthwhile testing jointly whether the average effect sizes across all events are larger closer to the event date. This can help to overcome limited temporal variation in some life events and provide a more general test of the adaptation hypothesis. Indeed, the average absolute effect size from the BUC estimates across the six life events 0-3 months after the event date is statistically significantly larger than the estimates for 2-3+ years (p=0.025). This is also true when comparing 0-6 months to 2-3+ years (p=0.020) and the difference is marginally significant when comparing 0-12 months to 2-3+ years (p=0.086).

An important question is whether the effect sizes in Table 5 and Figure 3 are economically meaningful. This is difficult to gauge from the ORs and marginal effects alone. If life events

[12]The first alternative I consider is whether the person reports difficulty gripping things in the current year but did not report any difficulty in the previous year. This is based on Decker and Schmidtz (2016), who use large changes in measured grip strength as a proxy for health shocks, arguing that grip strength is a strong indicator of overall health. Next I use self-assessed perceptions of own health today compared to one year ago. I treat the response 'much worse now than one year ago' as an adverse health shock and 'much better now than one year ago' as a favorable shock. Considering both favorable and unfavorable health shocks is unusual in this literature so is interesting in and of itself. None of the estimated coefficients are economically large or statistically significant (see Table C5).

only affect risk taking behavior through risk preferences, it would in principle be possible to use these events as instrumental variables. However, it is possible that life events also influence risk taking independently of risk preferences. The results in Table 3 – looking at the correlation between risk preferences and certain risk taking behaviors conditional on various personal characteristics – provide some suggestive evidence about the magnitude of the estimates. For example, based on Tobit regression on the share of equities to total assets, being in a higher risk taking class increases the probability of owning some equities by 13.3 percentage points (28.7%) and the proportion of equities held conditional on having some equities by 1.9 percentage points (23.3%).[13] While this implies potentially large effects for some individuals, the aggregate effect sizes are likely to be relatively modest. For example, based on results in Figure 3, 3-6 months after an improvement in finances risk willingness is estimated to be 0.12 standard deviations higher. This implies an increase in the probability of owning equities of 1.1 percentage points (2.3%) and on the proportion of equities held conditional on having some equities of 0.15 percentage points (1.9%).

One final statistic worth discussing is the amount of variance in the error term explained by individual fixed effects. In the linear fixed effects regression, this estimate is 58.5%. While the coefficients on life events imply an important role for these experiences, there is clearly also a strong stable component to risk preferences in adulthood.

5.2 Mechanisms

The conceptual framework in Section 2 sets out two broad channels through which life events can influence risk preferences – consumption and changes in the current state of the world that affect the parameters of the utility function, potentially through channels such as emotions, mood, mental health, biological responses and so on. Such state dependence can be thought of equivocally as changes in the marginal utility of consumption under a single parameter utility function. In this Section I test whether changes in wealth, the marginal

[13]These results are based on unreported Tobit regressions on the raw risk preference value, rather than the standardized value as reported in Table 3.

utility of consumption or mood and mental health are likely channels for the estimated relationships between life events and risk preferences.

To test the effect of consumption I use a basic mediation approach in which variables capturing this potential mediator are added to the baseline regression model and the resulting changes to the estimates of interest are examined. Note that the baseline model already controls for self-assessed changes in finances through the life event variables. However, this may not fully capture deviations in the consumption possibilities of individuals. In the HILDA survey, respondents are asked to recall their spending on a broad range of household goods and services over the past month, which are extrapolated to an annual figure. The expenditure categories are not exhaustive, for example there is limited time series information on luxury goods or one-off items like motor vehicles. However, they do cover a broad range of regular discretionary items, specifically alcohol, cigarettes, tobacco, clothing and footwear for children and adults, childcare fees, education fees, groceries, fees paid to health practitioners, home repairs and maintenance, meals eaten out, motor vehicle fuel, motor vehicle repairs, insurance fees, public transport and taxis, medicines, prescriptions and pharmaceuticals, telephone and internet fees, household utilities and rent. For home-owners, a measure of imputed rent is needed. I use the self-reported house value and assume a rent-to-price ratio of 1500:1 (i.e. imputed annual rent = 52*house value/1500), which is in line with the median observed ratio for Australia during the sample period (ABS, 2015).[14]

Since the consumption data are imperfect, I also use controls for household disposable income and indicators for self-assessed material wellbeing, which include the ability to raise a moderate sum of money and prosperity relative to personal circumstances.[15] The resulting estimates are plotted in Figure 4.[16]

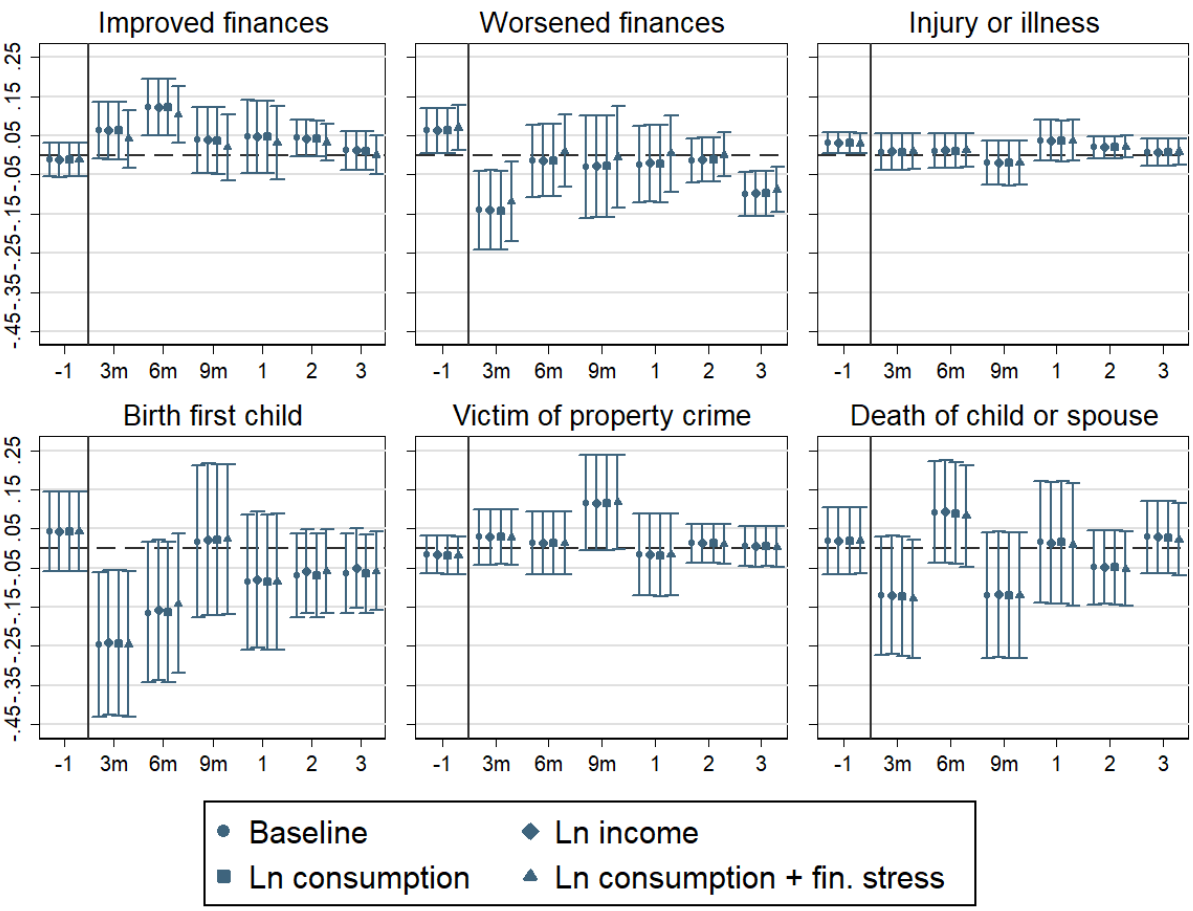
While household income is a significant predictor of risk preferences (see Table D1), it

[14]As for income, expenditure details are occasionally missing in the HILDA data and rather than dropping these observations I use the supplied imputed values. Just under 9% of household value observations are imputed; for the other expenditure items, imputation rates vary but are never above 4.4%.

[15]Further details are in Figure 4.

[16]For consistency with other figures in the paper, marginal effects from linear fixed effects regression are reported. Results from the BUC estimator are qualitatively similar.

Figure 4: Marginal effects: Mediation effect of material wellbeing variables



Note: N= 38,101 (4,810 individuals). T= 2006, 2008, 2010-2015. The estimates are marginal effects (with 95% confidence intervals) from an OLS fixed effects regression on risk preferences (standardized) in the financial domain [1-4 scale]. The sample size is slightly smaller than for the main regression results because observations are dropped if household income is negative or if the financial means variables are missing. The 'Ln income' model includes a control for current (log) household disposable income. The 'Ln consumption' model includes a control for current (log) equivalized household consumption. The 'Ln consumption + financial stress' model controls for equivalized household consumption as well as a full factorial for the following i) difficulty in raising \$2000 (\$3000 in wave 9+) and ii) self-assessed prosperity given current needs and financial responsibilities. There are four possible responses to (i): "Could easily raise emergency funds"; "Could raise emergency funds, but it would involve some sacrifice"; "Would have to do something drastic to raise emergency funds"; and "Couldn't raise emergency funds". There are six possible responses to (ii): "Prosperous"; "Very comfortable"; "Reasonably comfortable"; "Just getting along"; "Poor"; and "Very poor". The full regression results are in Table D1.

has almost no influence on the magnitude of the marginal effects. Only when controls for self-assessed material wellbeing are included is there a small attenuation in some of the estimates. This is mainly in the case of improvements/worsening in finances. For example, the marginal effect for 3-6 months after an improvement in finances decreases by 16.3%; for 0-3 months after a worsening in finances the estimate increases by 15.6%. There are similar degrees of attenuation for other estimates. However, in all cases the significance of the marginal effects remains unchanged and confidence intervals include the baseline estimates. The fact that even conditional on consumption and financial wellbeing the estimates for improvements/worsening in finances remain significant suggest that these results are not simply driven by the direct relationship between C and risk preferences in equation (2).

Next I turn to state dependence and more specifically changes in the marginal utility of consumption. People should be more (less) willing to take risks when their marginal utility of consumption is high (low).[17] For this to explain the results, we would therefore expect that favorable changes in finances increase the marginal utility of consumption, while adverse financial circumstances, parenthood and the death of a spouse or child lower the marginal utility of consumption, at least in the short run. Intuitively, this pattern of results seems plausible. The link between stressful life events and depressive symptoms is well established (Kessler, 1997; Tennant, 2002). Life events have also been linked to changes in measured affect, such as self-reported happiness and wellbeing (Luhmann et al., 2012), and sustained negative affect (depression) is associated with decreased sensitivity to rewards (see Hasler et al., 2004). In the case of parenthood, children may create new rivalry in consumption.

To test whether life events change the marginal utility of consumption I follow Finkelstein et al. (2013) by treating subjective wellbeing (SWB) as a proxy for experienced utility and test for state dependence by interacting life event variables with household consumption. Specifically, I estimate the following function:

[17] Note that for a concave utility function, if $U'(C)$ is larger in value in the new state of the world then it must be true that the new utility curve is always steeper than the old curve. This implies that marginal utility is decreasing more slowly in the new state of the world (i.e. $|U''(C)|$ is smaller). It follows from equation (2) that higher (lower) marginal utility of consumption would decrease (increase) risk aversion.

$$SWB_{it} = \sum_{l} \sum_{\rho=-(1-0)}^{2-3+} \beta_1^{\rho l} \gamma_{it}^{\rho l} + \sum_{l} \sum_{\rho=-(1-0)}^{2-3+} \beta_2^{\rho l} \gamma_{it}^{\rho l} C_i + \beta_3 C_i + x_{it}^{'} \dot{\delta} + \dot{\alpha}_i + \dot{\epsilon}_{it} \quad i = 1, \ldots, N; t = 1, \ldots, T \tag{4}$$

The dependent variable is a continuous measure of SWB – "All things considered, how satisfied are you with your life?" – which ranges from 0 (extremely dissatisfied) to 10 (extremely satisfied). C_i is log household consumption (equivalized) and β_3 reflects the marginal utility of consumption.[18] The intuition for equation (4) is that if life events influence the marginal utility of consumption then this will show up as disproportionate utility responses to life events between those with high consumption and low consumption, provided that low and high consumption people have the same utility function. If responses are not disproportionate, then a positive (negative) life event may result in a parallel shift up (down) of the utility function, but this would not affect the curvature.[19] The use of panel data is helpful as it allows me to control for unobserved time invariant heterogeneity that may be correlated with SWB and the likelihood of various life events occurring. Nevertheless, it is important to note that time variant heterogeneity correlated with the life events, as well as measurement error for consumption, may bias the estimates (the latter is likely to attenuate the estimates). Further, the model assumes that self-reported experiences are the same for different consumption types. This is reasonable for events like parenthood and death of a spouse or child but is potentially problematic for subjective life events. For example, the sort of economic shocks that underlie changes in financial circumstances may differ between high and low consumption types and this might be related to the magnitude of utility shifts.

[18]The first adult household member receives an equivalence value of one, additional household members aged 15 years and over receive 0.5 and children aged 0-14 years receive 0.3.

[19]Finkelstein et al. (2013) control for permanent household income rather than consumption. This makes more sense for their sample, since they study people who are retirement age and are likely to be relatively stable in their consumption patterns and family composition. Household consumption is conceptually stronger but is likely to be more prone to measurement error than income. A significant advantage of controlling directly for consumption, rather than permanent income (which is constant across time), is that I do not need to assume that life events have no direct or indirect effect on consumption. Any effect from consumption shifts on risk preferences is controlled for by C_{it} in equation (4).

The main interest is on the vector of coefficients $\beta_2^{\rho l}$, which reflect the additional utility of consumption conditional on having experienced the relevant life event ρ periods ago. Positive (negative) values on these interactions indicate higher (lower) marginal utility of consumption in the given state of the world. Higher marginal utility of consumption should lead to greater willingness to take risks, so the coefficients in $\beta_2^{\rho l}$ should closely follow the marginal effects presented in Figure 3 if the results are driven by changes in the marginal utility of consumption. I estimate equation (4) using linear fixed effects regression.

The full set of estimates from equation (4) are in Appendix D (Table D3). The primary interest is in the estimates $\hat{\beta}_2^{\rho l}$, which are reported in Figure 5.

For changes in financial circumstances and parenthood, there is little evidence that changes in the marginal utility of consumption coincide with changes in risk preferences. The dynamics in marginal utility do not match those for risk preferences and none of the estimates are statistically significant at the 5% level. The only estimates that provide some support for this mechanism are for the death of a spouse or child. There is a large decrease in the marginal utility of consumption immediately after this event, which coincides with increased risk aversion in Figure 3, although that estimate is not statistically significant. The marginally significant increase in risk aversion after 6-9 months also shadows the change in risk preferences. However, the increase in marginal utility after 2-3 years does not. Altogether, there is limited evidence to support the marginal utility of consumption channel.

The failure to find a strong role for the mechanisms identified in Section 2 suggests that something outside the traditional framework of expected utility theory might be driving the results. In Section 2, emotions, mood and mental health were discussed as possible underlying factors for state dependence. However, these factors may exert independent effects on risk attitudes. Loewenstein et al. (2001) emphasize the importance of emotions as key determinants of risky decision making that operate outside the realm of a well-behaved utility function. Adverse life events have been linked to increased risk of depression (Kendler et al., 1999). At the same time, depressive symptoms are associated with cognitive

Figure 5: Marginal effects: Marginal utility of income and life events

Note: N= 38,468 (4,810 individuals). T= 2006, 2008, 2010-2015. The estimates are marginal effects (with 95% confidence intervals) from an OLS fixed effects regression on the standardized value of life satisfaction [0-10 scale]. The marginal effects correspond to interaction terms between the relevant life event and (log) equivalized household consumption (inclusive imputed values). The sample size is slightly smaller than for the main regression results because observations are dropped if SWB is missing. The full regression results are in Table D3.

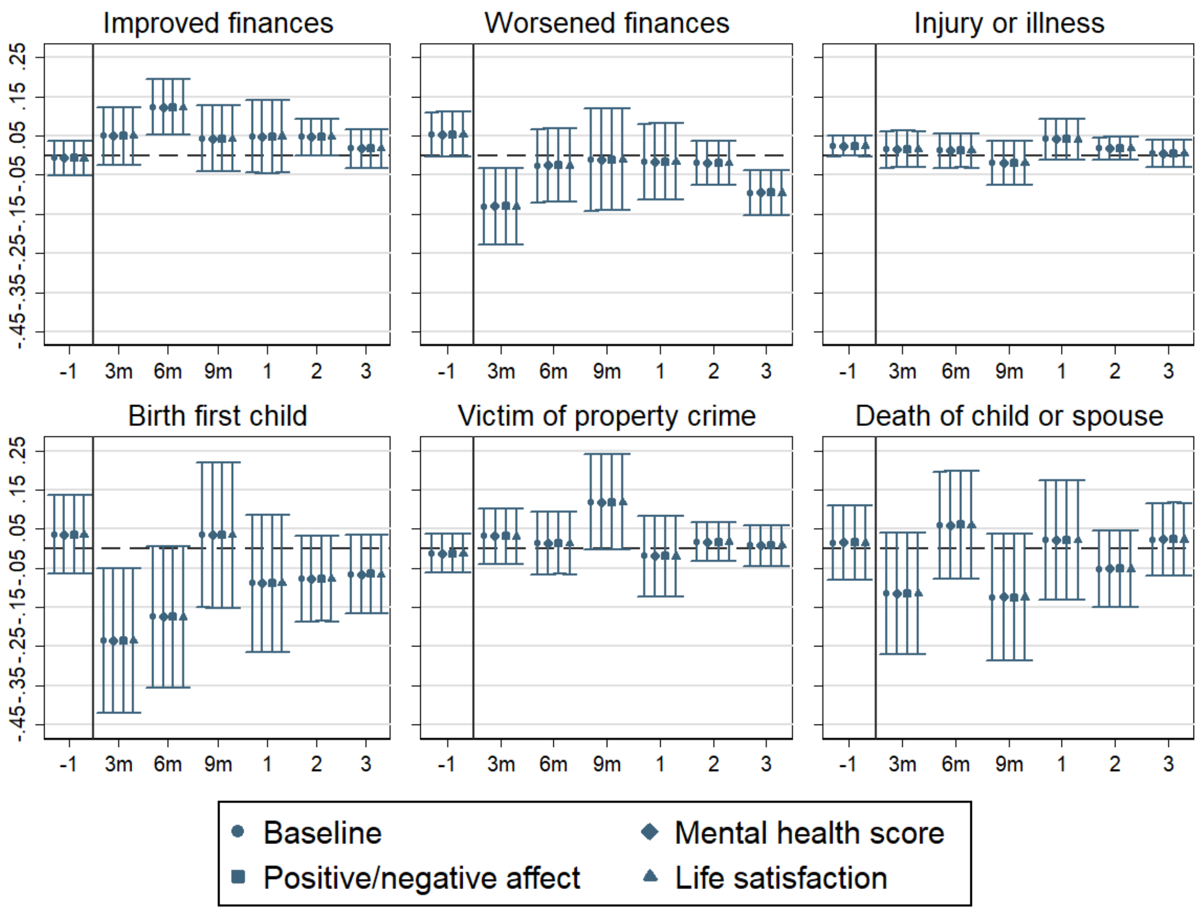
deficiencies, impairments in memory, fixation on negative outcomes and reduced reward sensitivity (see Hasler et al., 2004; Hammar & Årdal, 2009; Gotlib & Joorman, 2010; Chen et al., 2015, for reviews); each may affect propensity towards risky financial choices. Haushofer and Fehr (2014) argue that negative life shocks may lead to adverse mental health, stress and negative affect, which in turn can lead to greater risk aversion and failure to act on risky opportunities.

While there is limited time series information on fear and stress in the HILDA data, the survey does collect detailed information on mental health and mood each year. The SF-36 is included as part of the self-completion section of the survey. The SF-36 is a widely used, comprehensive health questionnaire that includes a subset of questions on mental health. These responses are used to create a mental health index score ranging between 0-100, with higher values corresponding to better mental health (see Ware et al., 2000). For the current sample, the mean of this index is 76.3 (s.d. 16.3). I first consider whether controlling for the SF-36 mental health score mediates the main results. Next I focus on positive/negative affect by only using a subset of responses to the SF-36. Specifically, I control for the individual means for the two questions targeting feelings of positive affect and the three questions targeting negative affect. Finally, I use the continuous measure of SWB [0-10 scale] described above. Results from this mediation analysis are reported in Figure 6.

Despite a strong conceptual basis for considering mental health and mood as important mediators, all measures of mental health, mood and SWB are statistically insignificant predictors of risk preferences. Unsurprisingly, including them in the regressions has virtually no impact on the point estimates for the life events variables.

Although the results in Figure 6 imply no mediating effect for mental health or mood, it is still possible that emotions and psychological factors outside the standard expected utility model are important. First, it is possible that other emotions and feelings, such as stress and fear, are mechanisms but these are not captured by the SF-36 questionnaire. Second, it is possible that the causal chain of events assumed by the regression model does not reflect the true process. The regression model assumes that risk preferences today are determined by mental health and mood today. It is possible that life events temporarily heighten emotions, which leads to longer lasting changes in risk preferences due to path dependent behavior, for example. Alternatively, in the framework of a dual-systems model for decision making under uncertainty (Loewenstein et al., 2001), experience with life events may increase the probability that risky decisions are driven by the affective system. Without a strong intuition for the causal chain, and with only annual observations, it is difficult to

Figure 6: Marginal effects: Mediation effect of mental health and mood



Note: N= 38,014, (4,810 individuals). T= 2006, 2008, 2010-2015. The estimates are marginal effects (with 95% confidence intervals) from an OLS fixed effects regression on risk preferences (standardized) in the financial domain [1-4 scale]. The sample size is slightly smaller than for the main regression results because observations are dropped if mental health, positive/negative affect or SWB are missing. The 'Mental health score' model includes a control for the SF-36 mental health component score. The 'Positive/negative affect' model includes controls for the likert responses of the two statements in the SF-36 targeting positive affect ("Felt calm and peaceful"; "Been a happy person") and the three questions targeting negative affect ("Been a nervous person"; "Felt so down in the dumps nothing could cheer you up"; "Felt down"). These are answered on a scale 1 (all of the time) to 6 (none of the time). The 'Life satisfaction' model controls for standardized answers to "All things considered, how satisfied are you with your life?" – which ranges from 0 (extremely dissatisfied) to 10 (extremely satisfied). The full regression results are in Table D2.

explore these possibilities directly. A different approach is to consider whether those who are more (less) emotionally stable are less (more) likely to be affected by life events. The response to aversive stimuli of people with lower emotional stability (neuroticism) is more likely to be dictated by their emotions (e.g. Vogeltanz & Hecker, 1999; Norris et al., 2007; Reynaud et al., 2012). Indeed, several studies demonstrate experimentally the causal effect of emotional regulation on choices in risky decision tasks (Leith & Baumeister, 1996; Heilman et al., 2010; Martin & Delgado, 2011). Callen et al. (2014) also suggest the importance of emotions by demonstrating that recalling a fearful event leads to greater preference for certainty for people exposed to terrorist attacks. Consequently, emotional stability may be a moderator and differences in risk preference responses across the emotional stability continuum could indicate a mechanistic role for emotions.

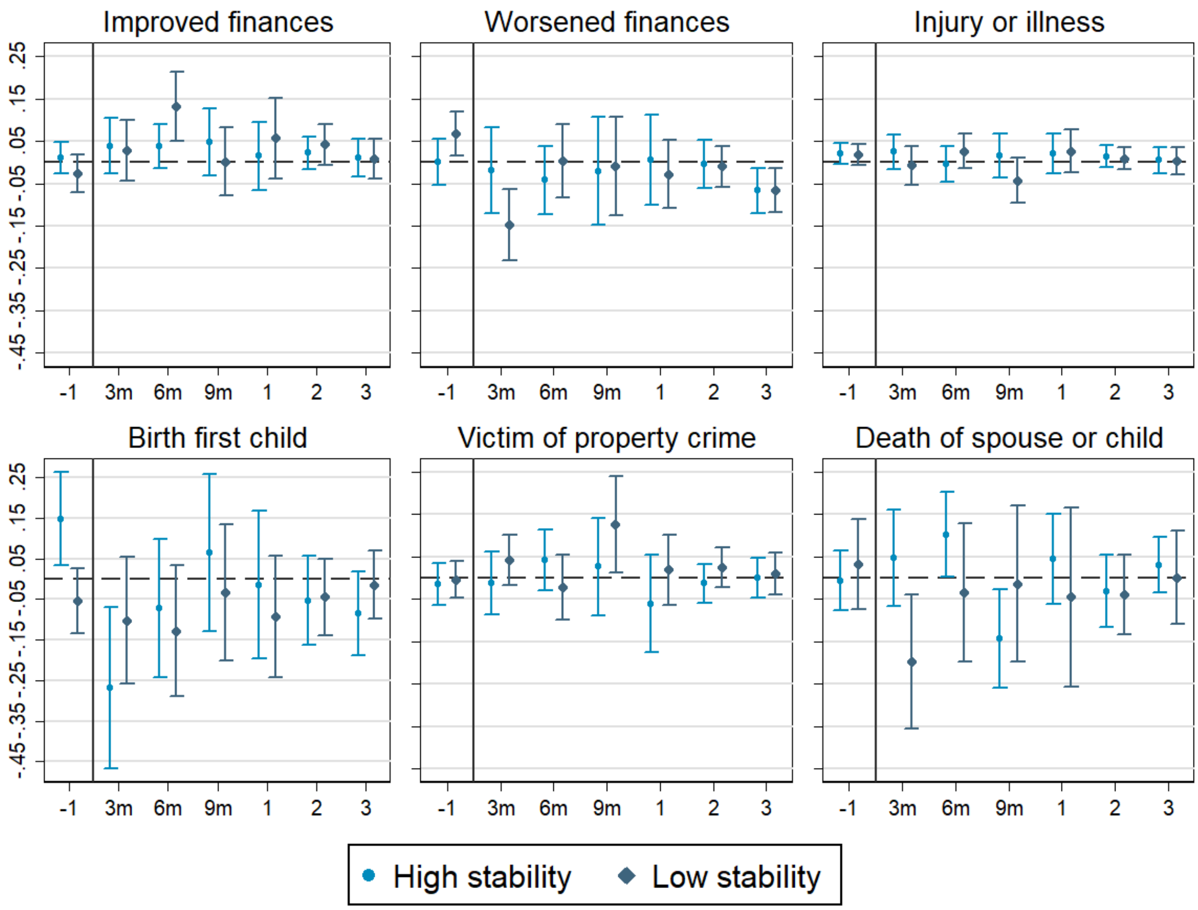
Information on emotional stability is available in the 2005, 2009 and 2013 waves of HILDA. Respondents completed a version of the Big-Five personality questionnaire based on Saucier (1994). For emotional stability, a scale is created for each of these years by taking the mean value for the following items (reversed scale): envious; moody; touchy; jealous; temperamental; and fretful (see Summerfield et al., 2017, for further details). This results in a scale of emotional stability ranging from 1 (unstable) to 7 (stable). In order to categorize people as either high or low emotional stability I take the average value of emotional stability across the three years and group people as above/below median stability.[20]

I estimate Equation (3) with the life event indicators interacted with being low/high emotional stability in order to get separate estimates for these two groups. The marginal effects from linear OLS regression are reported in Figure 7. There is consistent evidence for emotional stability having a moderating effect. The increase in risk willingness following an improvement in finances after 3-6 months is around twice as large for the low stability group and is not significantly different from zero for the high stability group. Similarly, the increase in risk aversion 0-3 months after a worsening in finances is only apparent for the low stability group. The increase in risk aversion 0-3 months after the death of a spouse or child is also only present for the low stability group. This is consistent with emotional regulation playing a moderating role in whether risk preferences change after these events.

[20] One concern is that emotional stability may change over time and this might be related to the experience of different life events. However, Cobb-Clark and Schurer (2012) explore the stability of personality variables using the HILDA data and find that changes in emotional stability over time are economically small and largely unrelated to life events (see also Lucas & Donnellan, 2011).

Interestingly, changes in risk preferences are more pronounced for the high stability group in the case of parenthood. In particular, this group is more risk willing leading up to the birth and experience a much larger decrease immediately after the birth. This again suggests that emotional stability is an important moderator but that the interaction between stability and life events may depend on the nature of the event.

Figure 7: Marginal effects: Main results by emotional stability



Note: N= 38,480 (4,810 individuals). T= 2006, 2008, 2010-2015. The estimates are marginal effects (with 95% confidence intervals) from an OLS fixed effects regression on risk preferences (standardized) in the financial domain [1-4 scale]. The marginal effects correspond to interaction terms between the relevant life event and low (below median) or high (above or equal median) emotional stability. Emotional stability is determined according to the within-person mean from the emotional stability (neuroticism) component of the Big Five questionnaire contained in the HILDA survey in the years 2005, 2009 and 2013 (in the case of missing values, available years are used).

To summarize, the analysis offers little support for the idea that life events shift risk preferences through changes in consumption levels or the marginal utility of consumption. Mental health and mood also have no mediating effect on the estimates. However, people who are more prone to having their behavior dictated by their emotions (i.e. those with low emotional stability) do in many cases have a stronger response to life events. This indicates that the feelings associated with life events may determine whether those events shift risk preferences. It would be helpful in future work to explore which emotions are influential and investigate the underlying psychological process in greater detail.

5.3 Gender differences

It is commonly found that females are more risk averse than males (Croson & Gneezy, 2009). It is unclear whether there are gender specific effects in the way preferences respond to common life events.[21] The experience of certain life events is likely to differ significantly across genders and this could give rise to heterogeneous responses in terms of risk preferences. For example, fatherhood differs from motherhood and there is evidence males experience a larger emotional response to the loss of a spouse (e.g. van Grootheest et al., 1999; Lee et al., 2001). To explore this, I estimate the main regression model with the additional controls for the life event indicators interacted with a male indicator. The results are presented in Table 6.

Because the sample sizes are often small for gender-event-period cells, the estimates are often imprecise when split by gender. I focus on life event indicators interacted with being male in Table 6, which test for gender differences. Note the overall OR for males can be recovered by multiplying the interaction effects with the baseline effects.[22] Overall, while some of the interaction terms are economically large, there are few statistically significant differences. One difference is with regards to worsening finances; we see that the sustained increase in risk aversion 2-3+ years after the event is restricted to females.

[21] Although different in nature to events studied here, Hanaoka et al. (2018) find that men in areas more affected by an earthquake in Japan became less risk averse, while women's preferences were not affected.

[22] For example, the overall OR for a male who experienced a financial improvement 0-3 months ago is $1.362 \times 0.834 = 1.136$.

Table 6: Regression results: With gender interactions

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
OR estimates for females (baseline group)						
0-1 year before	0.952	1.118	1.063	1.058	1.087	1.541
	(0.117)	(0.162)	(0.089)	(0.268)	(0.167)	(0.418)
0-3 months after	1.362	0.700	1.063	0.365*	1.103	0.445*
	(0.275)	(0.229)	(0.153)	(0.223)	(0.227)	(0.219)
3-6 months after	1.528**	1.029	1.120	0.837	1.220	2.004*
	(0.258)	(0.243)	(0.162)	(0.366)	(0.268)	(0.802)
6-9 months after	1.222	0.827	0.976	1.871	1.276	0.747
	(0.282)	(0.301)	(0.188)	(1.138)	(0.437)	(0.372)
9-12 months after	1.382	0.742	1.035	0.490	1.031	1.755
	(0.374)	(0.195)	(0.157)	(0.225)	(0.344)	(0.909)
1-2 years after	1.276*	0.862	1.146	0.933	1.140	0.742
	(0.164)	(0.126)	(0.102)	(0.242)	(0.153)	(0.230)
2-3+ years after	1.152	0.571***	1.048	0.997	0.937	1.086
	(0.157)	(0.085)	(0.106)	(0.239)	(0.137)	(0.281)
OR estimates interaction with male dummy						
0-1 year before	1.037	1.184	1.148	1.148	0.792	0.426**
	(0.180)	(0.241)	(0.133)	(0.418)	(0.154)	(0.168)
0-3 months after	0.834	0.741	0.940	1.093	1.037	1.680
	(0.231)	(0.302)	(0.194)	(0.837)	(0.282)	(1.249)
3-6 months after	1.040	0.789	0.937	0.345	0.730	0.373
	(0.275)	(0.257)	(0.184)	(0.231)	(0.219)	(0.253)
6-9 months after	0.929	1.315	0.895	0.351	1.260	0.329
	(0.344)	(0.673)	(0.236)	(0.260)	(0.546)	(0.313)
9-12 months after	0.833	1.431	1.258	2.360	0.834	0.195**
	(0.332)	(0.522)	(0.280)	(1.558)	(0.361)	(0.147)
1-2 years after	0.942	1.211	0.922	0.653	0.868	1.124
	(0.178)	(0.242)	(0.116)	(0.259)	(0.165)	(0.502)
2-3+ years after	0.897	1.429*	0.958	0.593	1.212	0.947
	(0.173)	(0.296)	(0.132)	(0.201)	(0.240)	(0.421)

Note: N= 31,736. T= 2006, 2008, 2010-2015. Sample only includes males. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. See Table 5 for additional details.

The main point of difference is with the response to the death of a spouse or child. Males become more risk averse in anticipation of this event and experience a larger and more stable increase in risk aversion across the first year after the event. The results for females are less stable; there is an increase in risk aversion 0-3 months after the event and an increase in risk willingness 3-6 months after the event. Given that these estimates are identified by different respondents, this instability should be interpreted carefully – overall, there is no strong evidence that these events either increase risk willingness or aversion. The apparent asymmetry between males and females might reflect different roles within the household. For example, since the risk preferences question is directly related to financial decisions, if males are more likely to be making these decisions then the question is more relevant to them. Similarly, females are already more likely to be in a low risk category (see Table 2) – age also lowers risk aversion and increases the risk of losing a spouse – consequently females may have little room to adjust their risk preferences further down. This is supported by the fact that in the year before the loss of a spouse 65% of females are in the lowest risk preference category compared to 48% for males.

5.4 General domain

As a final exercise I estimate the effect of life events on an alternative measure of risk preferences, namely the general risk attitude question asked in 2014 and discussed in Section 3. This recognizes some limitations with the Survey of Consumer Finance (SCF) measure used as the primary instrument in this paper. First, the SCF measure is elicited in respect of financial decisions rather than general willingness to take risks. It may therefore not adequately capture risk taking behavior outside this domain. Second, the SCF instrument has only four risk preference categories and a more granular measure may be better able to pick up variation in preferences across individuals. Third, the SCF instrument asks directly about actual financial behavior (except for the subset of hypothetical responses) rather than abstractly about attitudes towards taking risks. While actual financial behavior should be strongly influenced by risk preferences, there may also be other determinants. While these criticisms do not imply that the SCF instrument is inferior to the general risk attitude measure, they do motivate sensitivity analysis with this alternative.

The fact that the general risk attitude question is only asked in a single year is a significant constraint to utilizing this variable. This means that I can no longer 'transform out' the unobserved individual specific heterogeneity. One approach would be to assume that, conditional on covariates, unobserved heterogeneity is unrelated to life events. However, this is a strong assumption; it is likely that unobserved characteristics influence an individual's propensity to experience various life events. Instead, I propose a novel solution to controlling for unobserved heterogeneity based on the idea that risk preferences in different domains exert a common fixed effect (up to scale). More formally, assume that risk preferences in the general domain are given by

$$\tilde{y}^*_{it} = \sum_l \sum_{\rho=-(1-0)}^{2-3+} \tilde{\beta}^{\rho l} \tilde{\gamma}^{\rho l}_{it} + x'_{it}\tilde{\delta} + \sigma\alpha_i + \tilde{\epsilon}_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{5}$$

The individual fixed effect α_i is common to both equations (3) and (5), which assumes that any differences in risk preferences across domains are driven by the unequal effect of time varying covariates (x_{it}), life events (l) or idiosyncratic error on domain specific risk preferences. The parameter σ is a scale term. If y_{it} and $\tilde{y}_{it}$ are measured on the same scale and α_i exerts the same influence in both equations then $\sigma = 1$. In my estimation, y_{it} and $\tilde{y}_{it}$ are standardized values so this implies that a marginal change in α_i has an identical impact on the risk preference value in both domains in terms of standard deviation units.

While the assumption of a common fixed effect in equation (5) may seem strong, it is supported by recent experimental work that finds a common underlying preference across a myriad of elicitation tasks in different domains (Frey et al., 2017). It is also consistent with the way that economists typically treat risk preferences in applied and theoretical work, namely that risk preferences elicited in one context can be used to predict behavior in a different context. To demonstrate the critical assumption, imagine that individual i faces two gambles, one in the financial domain and one in the health domain. The gambles have equivalent risks and pay-offs when converted to a common monetary unit. Equation (5) assumes that if the agent behaves differently in the two gambles, this must be due to domain specific effects in the relationship between covariates and risk preferences (i.e. $\tilde{\beta}^{\rho l} \neq \beta^{\rho l}$ or $\tilde{\delta} \neq \delta$) or random error, not the agent's innate preference for risk.

I estimate equation (5) using a two-stage procedure where α_i is estimated in the first stage and then included as a regressor in the second stage. Estimating α_i is not straightforward. The approach I use is to estimate equation (3) by linear fixed effects regression and then back out the individual specific fixed effects. It is necessary to use a linear specification in the first stage since $\hat{\alpha}_i$ cannot be recovered from the BUC estimator. If we estimate $\hat{\sigma}$ freely in the second stage we will get a biased estimate due to the incidental parameters problem – each $\hat{\alpha}_i$ is obtained from only a small number of observations and $\hat{\sigma}$ only approaches its true value as $T \to \infty$. To address this I assume that equations (3) and (5) are directly proportional so that $\sigma = 1$. In this case we can estimate $\tilde{\beta}^{\rho l}$ by estimating a constrained regression in the second stage. Given the assumptions involved in this procedure, the estimates should be treated with some caution and perhaps best interpreted as bias reducing compared to a regression that relies solely on the selection on observables assumption.

Before turning to the estimation results, it is informative to look at the frequencies for the life event variables for the 2014 sample (Table 7). The frequencies are much smaller than for the full sample and while the improved granularity of the general risk preference instrument may improve precision, the small frequencies for the life event variables works against this. Given these smaller frequencies, it is no longer feasible to estimate the first year effects by quarters since the event. Instead these are amalgamated into a single identifier for 0-1 year.

Results from the two-stage estimator are presented in Table 8. For comparison, results from standard OLS and from the two-stage estimator without constraining $\hat{\sigma}$ are presented in Appendix D in Table D4. Standard errors for the constrained model are calculated using

Table 7: Frequencies for life events: 2014 sample

Life event	When event occurred -(0-1) year	0-1 year	1-2 years	2-3+ years
Major improvement finances	161	170	150	1042
Major worsening finances	101	103	106	754
Serious personal injury or illness	487	470	408	1895
Birth first child	19	24	24	477
Victim property crime	116	124	131	1083
Death of spouse or child	43	37	27	247

Note: 4,794 individuals. Data are from the year 2014. The questions on life events are part of the self-completion questionnaire in the HILDA survey. Respondents are asked "Did any of these happen to you in the past 12 months".

clustered non-parametric bootstrap.

Although there is some evidence that individuals become more willing to take risk in the first year after an improvement in finances from the basic OLS and unconstrained two-stage models, this effect is not significant in the two-stage constrained regression. As in the financial domain, there is evidence that people are more willing to take risk in the year before a worsening in finances and after this event the coefficients are all negative although insignificant. The strongest result is for parenthood. The birth of a first child is associated with an increase in risk aversion that is particularly strong 1-2 years after the event (-0.5 standard deviation units). There is also some evidence of an anticipation effect when looking at the basic OLS and unconstrained two-stage estimation results. As with the financial domain, there is evidence of adaptation over time – the marginal effect is closest to zero and no longer significant 2-3+ years after the event. Death of a spouse or child and property crime are unrelated to risk preferences; the former result should be interpreted with caution since there are few observations to identify its effect (see Table 7).

Overall, the results using the general risk preference instrument are weaker than the main results (with the exception of parenthood). One reason for this is that the estimates are identified by less observations (since only one year of data are used). It is also likely that there is more noise in the general risk question due to respondents framing their responses based on different risk taking behaviors. A third possibility is that there are domain specific

Table 8: Regression results: General domain

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
0-1 year before	0.031	0.228**	0.022	-0.369	-0.114	0.056
	(0.079)	(0.101)	(0.048)	(0.242)	(0.093)	(0.153)
0-1 year after	0.093	-0.034	0.010	-0.333	0.043	0.008
	(0.074)	(0.112)	(0.048)	(0.209)	(0.086)	(0.136)
1-2 years after	0.058	-0.081	0.079	-0.538***	0.062	-0.026
	(0.067)	(0.097)	(0.052)	(0.171)	(0.083)	(0.142)
2-3+ years after	-0.043	-0.042	0.052	-0.093	0.055	0.008
	(0.038)	(0.048)	(0.032)	(0.067)	(0.039)	(0.067)

Note: N= 4,794. T= 2006, 2008, 2010-2015. Coefficients from a two-step constrained OLS regression are reported. The dependent variable in the second stage is risk preferences in the general domain (standardized), measured on a 0-10 scale and elicited in wave 14 only. In the first stage, a linear fixed effects regression is estimated on risk preferences in the financial domain (standardized) measured on a 1-4 scale with the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple, a full set of year dummies and indicators for if a life event occurred -(0-1) year ago, 0-3 months ago, 3-6 months ago, 6-9 months ago, 9-12 months ago, 1-2 years ago or 2-3+ years ago for all of the life events in Table 4. In the second stage, the estimated vector of individual fixed effects ($\hat{\alpha}_i$) is included as an additional covariate along with age, age^2, overseas, university, diploma, student, region, employed, unemployed, retired, couple, male, mother secondary, father secondary and height. Clustered non-parametric bootstrap standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

responses to risk attitudes, which is an interesting question for future work.

6 Conclusion

This paper provides evidence that risk preferences are not independent of common life events. The events I study are particularly interesting because they are widely experienced – most people will experience one or more over their lifetime. The results suggest that changes in financial circumstances, parenthood and the death of a spouse or child are particularly influential. On the other hand, there is little evidence that health shocks or property crime affect risk preferences, even in the short-run.

A key finding is that people seem to be adaptive to life events in the sense that life events tend to exert the strongest influence close to the event date and the effects generally disappear over time. One hopeful property of this is that it may guard against reinforcing behavior, for example individuals experiencing a financial loss, becoming more risk averse, and failing to take advantage of profitable opportunities in the future. From a modelling perspective, the results do support a type of preference stability – one in which deviations in risk preferences over time are at least partly deterministic but preferences are tending towards an underlying mean (noting also that almost 60% of the variation in risk preferences is explained by individual fixed effects). They also suggest a more nuanced approach to controlling for life events in applied work. Failure to control for dynamics in the response function could help to explain mixed results in the literature.

In addition to focusing on dynamics, an important contribution of this paper is to explore mechanisms between life events and risk preferences. I find limited evidence that changes in consumption, the marginal utility of consumption, or mental health and mood explain the results. Instead, emotional stability is found to be an important moderator implying that emotions related to the experience of life events are influential. This is an important finding in terms of understanding how risk preferences are formed, how they evolve over the life-course, and who are most likely to have stable preferences over time.

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A Literature review

Table A1: Summaries of empirical studies of life events on risk preferences

Study	How risk preferences are measured	Sample	Estimation approach	Findings
Changes in finances				
Anderson et al. (2008)	Holt and Laury (2002) multiple price list (MPL) (incentivized).	Representative sample of Danish population 2003-2004. Follow up after 17 months. N=287.	Linear regression on the change in risk preferences.	People who became more risk willing more likely to self-report that finances improved.
Dohmen et al. (2016)	Risk willingness scale [0-10] framed in general domain.[a]	Representative samples from the German SOEP (2004-2011) and Ukrainian Longitudinal Monitoring Survey (2007 and 2012) aged 17-72. N=10,022 for Germany 2004-2009, N=7,809 for Germany 2006-2011 and N=3,456 for Ukraine 2007-2012.	Interval regression on the change in risk preferences.	Changes in household income not statistically significant. Improvements in household wealth relative to changes in financial position are associated with greater risk willingness in Ukraine but not Germany.
Guiso et al. (2017)	1. Risk willingness scale [1-4] framed in financial domain. 2. Variant of MPL (hypothetical).	Survey of Italian bank clients with at least 10,000 Euro in wealth in 2007. Follow up in 2009. N=666 (participants both waves).	Mean change in risk preferences.	After the Global Financial Crises, clients are more risk averse even if they experienced no loss.
Malmendier and Nagel (2011)	Risk willingness scale [1-4] framed in financial domain. Also uses actual financial behavior as outcome variables.	Repeated cross-sections from the U.S. Survey of Consumer Finance 1960-2007 (risk preference question only from 1983). N=28,571 (asked risk preference question).	Ordered probit regression (for risk preferences).	Individuals exposed to poor stock market performance throughout their lives are more risk averse, invest more conservatively and exhibit greater pessimism regarding future returns.
Paravisini et al. (2018)	Derived based on financial decisions in a person-to-person lending platform.	Investors in a U.S. person-to-person lending platform October 2007-April 2008. N=2,168.	Linear fixed effects regression.	Adverse housing wealth shocks are associated with greater risk aversion.

Sahm (2012)	Hypothetical gambles on lifetime income.	U.S. Health and Retirement Survey (HRS) 1992-2002 (age range 45-70). N=12,003.	Correlated random effects regression.	Income and wealth fluctuations not statistically significant.
Health				
Chuang Schechter (2015)	1. Hypothetical gamble questions (number of risky choices). 2. Incentivized gambling task (2002 only).	Field study in Paraguay. In 2002 participants completed an incentivized gambling task. In 2007 and 2009 they completed a hypothetical task. N=140 for 2007, N=49 for 2009.	Linear regression conditional on previous wave risk preference.	For 2007, number of days sick predicts greater risk aversion (marginally significant). For 2009, number of days sick predicts lower risk aversion.
Decker and Schmidtz (2016)	Risk willingness scale [0-10] framed in general domain.	Representative sub-sample from the German SOEP 2006-2014. N=6642.	Regression-adjusted matching estimation.	Large changes in grip strength associated with increased risk aversion that persists up to four years.
Dohmen et al. (2016)	Risk willingness scale [0-10] framed in general domain.[a]	Representative samples from the German SOEP (2004-2011) and Ukrainian Longitudinal Monitoring Survey (2007 and 2012) aged 17-72. N=10,022 for Germany 2004-2009, N=7,809 for Germany 2006-2011 and N=3,456 for Ukraine 2007-2012.	Interval regression on the change in risk preferences.	Self-assessed improvement in health associated with increased risk willingness in Germany for period 2004-2009 (insignificant for 2006-2011). Worsening health associated with increased risk aversion in Ukraine. Changes in disability status not statistically significant.
Gloede et al. (2015)	Risk willingness scale [0-10] framed in general domain.	Samples from three provinces in Northeast Thailand and three provinces in Vietnam in 2010. N=2,068 in Thailand, N=2048 in Vietnam.	Interval regression.	An indicator for illness or injury to a household member is associated with higher risk aversion in Vietnam but not Thailand.
Sahm (2012)	Hypothetical gambles on lifetime income.	U.S. HRS 1992-2002. N=12,003.	Correlated random effects regression.	Adverse health conditions (heart disease, stroke, cancer or lung disease) not statistically significant.
Parenthood				
Browne et al. (2016)	Risk willingness scale [0-10] framed in general domain.	Representative sample from the German SOEP (2004-2012) aged 18+. N=7,339.	Linear fixed effects regression.	Birth of a first child (if household head) associated with increased risk aversion. Insignificant for non-heads of household.

Görlitz and Tamm (2015)	Risk willingness scale [0-10] framed in general domain.	Representative sample from the German SOEP (2004-2012) aged 17-64. N=28,000.	Linear fixed effects regression.	Birth of a first child associated with increased risk aversion up to two years before the event and persisting for several years after the event for both men and women. Effect strongest closer to the birth.
Wang et al. (2009)	Questionnaire based on propensity to engage in risky behaviors across five separate domains: within-group competition; between-group competition; environmental challenge; mating; reproduction.	Student sample (University of South Dakota). N=448. Note: only 31 parents among student sample.	Correlation (conditional on age).	Parenthood associated with increased risk aversion in within-group competition and between-group competition domains.
Victim of property crime				
Chuang and Schechter (2015)	1. Hypothetical gamble questions (number of risky choices). 2. Incentivized gambling task (2002 only).	Field study in rural Paraguay. In 2002 participants completed an incentivized gambling task. In 2007 and 2009 they completed a hypothetical task. N=140 for 2007, N=49 for 2009.	Linear regression conditional on previous wave risk preference.	For 2007, changes in the amount of experienced theft in the last year (2007-2002) predicts greater risk willingness. For 2009, changes in the amount of experienced theft in the last year (2009-2007) is not statistically significant.
Death of a spouse or child				
Browne et al. (2016)	Risk willingness scale [0-10] framed in general domain.	Representative sample from the German SOEP (2004-2012) aged 18+. N=7,339.	Linear fixed effects regression.	Death of a spouse is not statistically significant.
Salamanca (2016)	Index based on six items related to financial risk taking.	Dutch National Bank Household Survey (1996-2015). N=2,894.	Dynamic GMM linear regression.	Being widowed is not statistically significant.

[a] The working paper version (Dohmen et al., 2015) includes some results for other domains (e.g. career, driving, finance, health, sport).

B Replacing self-assessed financial shocks with income shocks

B.1 Drivers of changes in financial circumstances

In this Appendix I explore the drivers of changes in financial circumstances before turning to more objective measures, namely changes in real household disposable income.

To explore the underlying drivers for each of these life events I regress (using a binary logit model) the contemporaneous experience of an improvement/worsening in finances on a variety of covariates that capture i) changes in wealth and ii) changes in household expenses. I hypothesize that improvements in finances are more strongly correlated with wealth while worsening finances are more likely to capture changes in expenses. The marginal effects from these regressions are presented in Table B1. For each type of change in finances, the first column includes all people in the sample, the second column includes singles only and the third column is restricted to the 2006 and 2010 samples only. This restriction is so that I can include an indicator for those whose current household bills exceed 1% of current household income. This is likely to be a good indicator of financial stress and information on household bills was only collected in these waves.[23]

Consistent with Au and Johnston (2015), I find that transfers are an important determinant of favorable changes in finances. The marginal effect for the full sample is 35.1 percentage points. For singles, this is the only significant covariate. For the full sample, there is a modest correlation with income, receiving dividends, changes in household value and health shocks. Overall, shocks more likely to result in permanent changes in wealth seem to play a relatively small role.

For unfavorable changes in finances, shocks on the expenses side seem to play an important role. Experiencing a health shock and being the victim of property crime increase the risk of worsening finances. Being a home owner reduces risk, perhaps indicating greater financial security for these people. Having a high bill to income ratio is associated with a large (6.3 percentage points) increase in the risk of worsening finances. Fluctuations in wealth also matter. Adverse income shocks, unemployment and receiving dividends all increase the risk of worsening finances.

This analysis reveals that the life event measures of improvements and worsening in finances are not reciprocal events. Improvements in finances is largely driven by transfers while worsening finances is strongly influenced by expenses. One advantage of these measures of financial shocks is that they capture this diversity in experiences. Moreover, the mere fact that people self-identify as having experienced these events indicates that the experience was meaningful. Nevertheless, it is useful to also examine more objective measures of changes in finances in order to better compare with the existing literature and to remove ambiguity about the underlying drivers. I turn to this now.

[23] 2.7% of individuals are in households that exceed this ratio.

Table B1: Drivers of changes in financial circumstances

	Finances improved			Finances worsened		
	All	Singles	2006, 2010	All	Singles	2006, 2010
Inc. imp.	0.007*	0.009	0.007	0.002	0.007	-0.003
	(0.004)	(0.007)	(0.006)	(0.003)	(0.008)	(0.005)
Inc. wor.	0.002	0.009	0.004	0.028***	0.038***	0.036***
	(0.005)	(0.007)	(0.007)	(0.006)	(0.011)	(0.010)
Rec. div.	0.004**	0.002	0.007**	-0.009***	-0.006	-0.009***
	(0.002)	(0.005)	(0.003)	(0.002)	(0.006)	(0.003)
Employed	0.001	0.003	0.000	-0.008***	-0.010*	-0.009***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)
Rec. transfer	0.351***	0.385***	0.297***	0.013**	0.024	0.014
	(0.015)	(0.032)	(0.022)	(0.006)	(0.015)	(0.009)
Home val. imp.	0.011***	0.015	0.009*	-0.001	-0.003	-0.000
	(0.004)	(0.009)	(0.005)	(0.003)	(0.010)	(0.005)
Home val. wor.	0.016**	0.006	0.031**	0.010	0.018	0.010
	(0.008)	(0.015)	(0.015)	(0.007)	(0.019)	(0.013)
Sick/injury	0.007**	0.010	0.009	0.040***	0.054***	0.036***
	(0.003)	(0.007)	(0.006)	(0.005)	(0.011)	(0.006)
Prop. Crime	0.003	0.000	0.001	0.027***	0.036**	0.026***
	(0.005)	(0.009)	(0.008)	(0.007)	(0.016)	(0.010)
Home owner	-0.000	-0.002	-0.000	-0.019***	-0.020***	-0.014***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)	(0.004)
Birth	0.001	0.033	0.014	0.005	-0.022	0.008
	(0.006)	(0.052)	(0.011)	(0.006)	(0.020)	(0.009)
HH bill high			0.000			0.079***
			(0.011)			(0.017)
Observations	38480	9607	14430	38480	9607	14430
Pseudo R^2	0.159	0.173	0.128	0.048	0.040	0.064

Note: In columns 2-4 (5-7) the dependent variable is an indicator for whether the individual reported that finances improved (worsened) in the last 12 months. Results are based on binary logit regressions and average marginal effects are reported. Inc. imp. (Inc. wor.) is an indicator for if real household disposable income increased (decreased) by at least 50% on the previous year. Rec. transfer is an indicator for if the individual received a lump sum transfer (e.g. bequest, redundancy). Home val. imp. (Home val. wor.) is an indicator for if the value of the own home increased (decreased) by at least 25% on the previous year. This indicator is set to zero when home value is missing in the previous year (< 2% of cases). Home owner is an indicator for being a home owner. Birth is an indicator for the birth or adoption of a child in the previous 12 months. HH bill high is an indicator for if the real value of current household bills exceeds 1% of current real household disposable income. Other variables are described in Tables 1 and 3. Cluster robust standard errors calculated using the delta method in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Alternative measures of financial shocks

A more objective measure of financial shocks is large changes in real household disposable income. In this section I replace the self-assessed indicators for changes in financial circumstances with indicators for large fluctuations in real household disposable income. I treat an income shock of ± 50% of last year's income as a baseline and consider the sensitivity of this by also estimating the model with a smaller (30%) and larger (70%) shock for comparison. In cases where household income is missing in the previous year (18% of observations) I act as if there was no financial shock.[24]. Note as well that since I only observe current annual income, I have less information on the timing of the financial shock than with the life event variables. I therefore only have indicators for if the shock occurred 0-1 year ago, 1-2 years ago or 2-3+ years ago (noting that surveys are completed at intervals of approximately one-year on average). The frequencies for these income shock variables are in Table B2 and the regression results are reported in Table B3.

Table B2: Frequencies for income shocks

	When event occurred			
Life event	-(0-1) year	0-1 year	1-2 years	2-3+ years
30% income improvement	3912	4395	4626	15053
50% income improvement	2312	2636	2768	9380
70% income improvement	1575	1850	1888	6577
30% income drop	3104	3499	3482	14482
50% income drop	1244	1377	1430	8495
70% income drop	508	525	543	5573

Note: Pooled sample size is 38,481 (4,810 individuals). Data are from the years 2006, 2008 and 2010-2015.

The results for positive financial shocks are weaker when using income shocks compared to the life event variable. The only statistically significant effect (at 5%) is after 1-2 years in the case of a 30% income shock. This effect is positive, consistent with the main results results (Table 5), and short-lived. The results for negative income shocks are more in-line with the life event variable. While not all effects are precisely estimated, looking across the rows of Table B2 there is evidence that negative income shocks are associated with greater risk willingness in the year before the event and greater risk aversion after the event and this is largely robust to different shock sizes. In contrast to the earlier results, there is a stronger indication of adaptation, in particular when restricting income shocks to be 70% of income in the previous 12 months.

These results may imply that the nature of the change in financial circumstances is important. Since the life event variable is strongly influenced by unanticipated exogenous increases in wealth, the evidence suggests that these shocks might matter more for preference formation than other income shocks, which are more likely to be anticipated or expected. When it comes to adverse financial shocks, income shocks seem to be more important. This

[24]This is a conservative approach since it biases the results towards zero.

Table B3: BUC estimation results around real income shocks

	Δ 50%		Δ 30%		Δ 70%	
	Inc. imp.	Inc. wor.	Inc. imp.	Inc. wor.	Inc. imp.	Inc. wor.
0-1 year before	0.967	1.079	0.982	1.074	0.976	1.077
	(0.070)	(0.092)	(0.054)	(0.064)	(0.080)	(0.136)
0-1 year after	0.951	0.958	1.038	0.962	0.912	0.758*
	(0.066)	(0.088)	(0.056)	(0.057)	(0.075)	(0.108)
1-2 years after	1.100	0.882	1.108**	0.869**	1.025	0.825
	(0.070)	(0.081)	(0.057)	(0.052)	(0.076)	(0.120)
2-3+ years after	1.003	0.919	1.062	0.895**	0.952	0.929
	(0.050)	(0.052)	(0.046)	(0.041)	(0.055)	(0.068)

Note: N= 31,736. T= 2006, 2008, 2010-2015. The estimation sample size is less than $N(4,968) \times T(8) \times K(3)$ because observations where outcomes do not vary over the period drop out of the likelihood function. Exponentiated coefficients (odds ratios) from three separate estimations of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. The main independent variables are changes in real household disposable income on the previous year. The estimations control for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. It also includes a full set of controls for other life events with indicators for if the event occurred -(0-1) year ago, 0-3 months ago, 3-6 months ago, 6-9 months ago, 9-12 months ago, 1-2 years ago or 2-3+ years ago. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

implies a degree of asymmetry in the way people respond to income shocks in terms of their risk preferences.

C Sensitivity analysis

Table C1: Main BUC estimation results excluding hypothetical responses

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
0-1 year before	0.980	1.335**	1.158**	0.934	0.940	1.049
	(0.092)	(0.161)	(0.077)	(0.176)	(0.102)	(0.245)
0-3 months after	1.402**	0.496***	1.055	0.352***	1.153	0.602
	(0.206)	(0.115)	(0.122)	(0.137)	(0.175)	(0.235)
3-6 months after	1.778***	0.778	1.073	0.473**	1.049	1.617
	(0.251)	(0.148)	(0.119)	(0.174)	(0.184)	(0.662)
6-9 months after	1.382*	1.139	1.011	1.237	1.541*	0.378*
	(0.269)	(0.347)	(0.150)	(0.464)	(0.374)	(0.192)
9-12 months after	1.394	0.991	1.057	0.813	1.043	1.032
	(0.304)	(0.224)	(0.131)	(0.291)	(0.235)	(0.432)
1-2 years after	1.343***	0.930	1.107	0.641**	1.022	0.800
	(0.136)	(0.117)	(0.080)	(0.144)	(0.110)	(0.206)
2-3+ years after	1.191	0.748**	1.046	0.665**	1.015	1.132
	(0.128)	(0.092)	(0.086)	(0.133)	(0.116)	(0.279)

Note: N= 26,118. T= 2006, 2008, 2010-2015. Exponentiated coefficients (odds ratios) from a single estimation of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. Observations where respondents initially answered the risk preference question with "I never have any spare cash" have been dropped from the estimation. The estimation controls for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C2: Main BUC estimation results excluding missing life event quarters

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
0-1 year before	1.051	1.311**	1.119*	1.176	0.900	1.060
	(0.107)	(0.165)	(0.074)	(0.237)	(0.100)	(0.266)
0-3 months after	1.280	0.529***	0.965	0.352***	1.140	0.673
	(0.200)	(0.121)	(0.115)	(0.138)	(0.181)	(0.299)
3-6 months after	1.528**	0.880	1.042	0.428**	1.203	1.982*
	(0.263)	(0.216)	(0.128)	(0.163)	(0.230)	(0.822)
6-9 months after	1.205	0.979	0.944	0.920	1.513*	0.518
	(0.243)	(0.279)	(0.143)	(0.345)	(0.359)	(0.274)
9-12 months after	1.426	0.858	1.087	0.903	1.095	0.595
	(0.309)	(0.205)	(0.139)	(0.305)	(0.253)	(0.224)
1-2 years after	1.273**	1.026	1.093	0.680*	1.002	0.911
	(0.139)	(0.134)	(0.083)	(0.153)	(0.111)	(0.270)
2-3+ years after	1.219	0.801	1.008	0.680*	1.082	0.932
	(0.147)	(0.111)	(0.084)	(0.138)	(0.129)	(0.251)

Note: N= 26,056. T= 2006, 2008, 2010-2015. Exponentiated coefficients (odds ratios) from a single estimation of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. Respondents are excluded from the estimation sample if at any point during 2004-2015 they indicate experiencing a life event in the previous 12 months but do not indicate in which quarter (i.e. 0-3, 3-6, 6-9 or 9-12 months ago) this occurred. The estimation controls for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Main BUC estimation results with aggregate first year effect

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
0-1 year before	0.966	1.233**	1.137**	1.109	0.948	1.075
	(0.084)	(0.126)	(0.066)	(0.198)	(0.090)	(0.218)
0-1 year after	1.352***	0.826*	1.059	0.612**	1.101	0.805
	(0.113)	(0.088)	(0.065)	(0.123)	(0.099)	(0.170)
1-2 years after	1.223**	0.984	1.112*	0.774	1.043	0.789
	(0.113)	(0.099)	(0.070)	(0.159)	(0.099)	(0.174)
2-3+ years after	1.096	0.707***	1.037	0.764	1.026	1.042
	(0.109)	(0.075)	(0.078)	(0.143)	(0.105)	(0.220)

Note: N= 31,736. T= 2006, 2008, 2010-2015. Exponentiated coefficients (odds ratios) from a single estimation of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. The estimation controls for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C4: Main BUC estimation results with immediate adaptation to old events

	Fin. imp.	Fin. wor.	Sick	Fbirth	Crime	Death
0-1 year before	0.961	1.244**	1.130**	1.146	0.937	1.145
	(0.082)	(0.131)	(0.065)	(0.209)	(0.090)	(0.235)
0-3 months after	1.252	0.526***	1.054	0.391**	1.103	0.610
	(0.182)	(0.110)	(0.124)	(0.147)	(0.171)	(0.233)
3-6 months after	1.609***	0.794	1.101	0.534*	1.029	1.417
	(0.230)	(0.144)	(0.122)	(0.184)	(0.172)	(0.496)
6-9 months after	1.319	0.826	0.953	0.991	1.343	0.530
	(0.252)	(0.225)	(0.134)	(0.359)	(0.300)	(0.236)
9-12 months after	1.341	0.786	1.207	0.653	0.851	0.922
	(0.275)	(0.154)	(0.156)	(0.232)	(0.193)	(0.366)
1-2 years after	1.311**	0.825	1.094	0.791	1.012	0.878
	(0.154)	(0.116)	(0.100)	(0.173)	(0.133)	(0.220)
2-3+ years after	1.051	0.690***	1.021	0.754	0.982	1.201
	(0.115)	(0.086)	(0.089)	(0.146)	(0.117)	(0.273)

Note: N= 31,736. T= 2006, 2008, 2010-2015. Exponentiated coefficients (odds ratios) from a single estimation of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. When a new life event occurs, respondents are assumed to immediately adapt to the previous event. For example, if in a given year a person experiences an improvement in finances and then the following year experiences a second improvement in finances, the indicators for the first event are set to zero, effectively assuming that people are only affected by the most recent event. The estimation controls for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. Cluster robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C5: Main BUC estimation results with alternative definitions of health shocks

	Grip wor.	Health wor.	Health imp.
0-1 year before	1.097	1.248	1.034
	(0.127)	(0.208)	(0.100)
0-1 year after	1.056	0.937	1.007
	(0.145)	(0.148)	(0.092)
1-2 years after	0.927	1.076	0.979
	(0.121)	(0.166)	(0.092)
2-3+ years after	0.952	0.943	0.945
	(0.115)	(0.128)	(0.072)

Note: N= 31,736. T= 2006, 2008, 2010-2015. Exponentiated coefficients (odds ratios) from a two separate estimations of the BUC ordered fixed effects logit model are reported. The dependent variable is risk preferences in the financial domain, measured on a 1-4 scale. The first estimation (column 2) replaces the life event indicator for a health shock with an indicator for if the respondent reports experiencing difficulty gripping things in the current wave but did not report this in the previous wave. In the second estimation (columns 3-4) an adverse health shocks is where respondents report that their health is 'much worse now than one year age'. A favorable health shock is where they report their health is 'much better now than one year ago'. Both estimation control for the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple as well as a full set of year dummies. It also includes a full set of controls for other life events with indicators for if the event occurred -(0-1) year ago, 0-3 months ago, 3-6 months ago, 6-9 months ago, 9-12 months ago, 1-2 years ago or 2-3+ years ago. Cluster robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Ancillary results

Table D1: Estimates from Figure 4: Wealth mediation

	(1) Baseline	(2) Ln income	(3) Ln consume	(4) Financial stress
Improved finances				
0-1 year before	-0.012	-0.013	-0.012	-0.011
	(0.022)	(0.022)	(0.022)	(0.022)
0-3 months after	0.063*	0.063*	0.063*	0.041
	(0.037)	(0.037)	(0.037)	(0.038)
3-6 months after	0.123***	0.122***	0.122***	0.103***
	(0.037)	(0.037)	(0.037)	(0.037)
6-9 months after	0.039	0.038	0.037	0.020
	(0.043)	(0.043)	(0.043)	(0.043)
9-12 months after	0.047	0.046	0.047	0.031
	(0.047)	(0.047)	(0.047)	(0.047)
1-2 years after	0.043*	0.043*	0.042*	0.032
	(0.024)	(0.024)	(0.024)	(0.024)
2-3+ years after	0.012	0.011	0.010	0.001
	(0.025)	(0.025)	(0.025)	(0.025)
Worsened finances				
0-1 year before	0.062**	0.062**	0.063**	0.070**
	(0.030)	(0.030)	(0.030)	(0.029)
0-3 months after	-0.141***	-0.140***	-0.141***	-0.119**
	(0.051)	(0.051)	(0.051)	(0.052)
3-6 months after	-0.016	-0.014	-0.014	0.010
	(0.047)	(0.047)	(0.047)	(0.047)
6-9 months after	-0.030	-0.029	-0.029	-0.005
	(0.066)	(0.066)	(0.066)	(0.067)
9-12 months after	-0.024	-0.020	-0.022	0.004
	(0.050)	(0.050)	(0.050)	(0.050)
1-2 years after	-0.014	-0.011	-0.012	0.001
	(0.028)	(0.029)	(0.029)	(0.029)
2-3+ years after	-0.100***	-0.098***	-0.097***	-0.088***
	(0.029)	(0.029)	(0.029)	(0.029)
Injury or illness				
0-1 year before	0.031**	0.031**	0.031**	0.030**
	(0.014)	(0.014)	(0.014)	(0.014)
0-3 months after	0.008	0.009	0.008	0.010
	(0.024)	(0.024)	(0.024)	(0.024)
3-6 months after	0.011	0.011	0.011	0.013
	(0.022)	(0.022)	(0.022)	(0.022)

6-9 months after	-0.020	-0.020	-0.021	-0.020
	(0.029)	(0.029)	(0.029)	(0.029)
9-12 months after	0.037	0.037	0.036	0.037
	(0.027)	(0.027)	(0.027)	(0.027)
1-2 years after	0.020	0.019	0.019	0.021
	(0.015)	(0.015)	(0.015)	(0.015)
2-3+ years after	0.007	0.007	0.007	0.009
	(0.018)	(0.018)	(0.018)	(0.018)
Birth first child				
0-1 year before	0.043	0.043	0.042	0.043
	(0.052)	(0.052)	(0.052)	(0.052)
0-3 months after	-0.245***	-0.240**	-0.242**	-0.245***
	(0.094)	(0.094)	(0.094)	(0.094)
3-6 months after	-0.165*	-0.158*	-0.163*	-0.141
	(0.091)	(0.091)	(0.091)	(0.091)
6-9 months after	0.017	0.023	0.020	0.023
	(0.099)	(0.099)	(0.098)	(0.098)
9-12 months after	-0.086	-0.081	-0.087	-0.086
	(0.088)	(0.088)	(0.088)	(0.088)
1-2 years after	-0.069	-0.059	-0.069	-0.059
	(0.055)	(0.055)	(0.055)	(0.054)
2-3+ years after	-0.064	-0.051	-0.065	-0.059
	(0.051)	(0.052)	(0.051)	(0.051)
Victim of property crime				
0-1 year before	-0.017	-0.017	-0.017	-0.019
	(0.025)	(0.025)	(0.025)	(0.025)
0-3 months after	0.028	0.028	0.029	0.028
	(0.036)	(0.036)	(0.036)	(0.036)
3-6 months after	0.014	0.014	0.014	0.014
	(0.041)	(0.041)	(0.041)	(0.041)
6-9 months after	0.116*	0.116*	0.116*	0.118*
	(0.062)	(0.062)	(0.062)	(0.062)
9-12 months after	-0.016	-0.017	-0.017	-0.016
	(0.053)	(0.053)	(0.053)	(0.053)
1-2 years after	0.013	0.012	0.013	0.010
	(0.026)	(0.025)	(0.026)	(0.026)
2-3+ years after	0.005	0.004	0.005	0.003
	(0.027)	(0.026)	(0.026)	(0.026)
Death of child or spouse				
0-1 year before	0.018	0.018	0.018	0.020
	(0.043)	(0.043)	(0.044)	(0.043)
0-3 months after	-0.121	-0.120	-0.123	-0.129*
	(0.077)	(0.077)	(0.077)	(0.077)

3-6 months after	0.091	0.094	0.089	0.082
	(0.066)	(0.066)	(0.066)	(0.066)
6-9 months after	-0.120	-0.117	-0.121	-0.120
	(0.082)	(0.081)	(0.082)	(0.082)
9-12 months after	0.016	0.014	0.015	0.009
	(0.079)	(0.079)	(0.079)	(0.080)
1-2 years after	-0.049	-0.048	-0.049	-0.053
	(0.048)	(0.048)	(0.048)	(0.048)
2-3+ years after	0.028	0.028	0.027	0.022
	(0.047)	(0.047)	(0.047)	(0.047)
Age sq	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
University	0.008	0.009	0.010	0.001
	(0.072)	(0.071)	(0.072)	(0.072)
Diploma	-0.004	-0.003	-0.002	-0.003
	(0.061)	(0.061)	(0.061)	(0.061)
Student	-0.066	-0.063	-0.065	-0.062
	(0.042)	(0.042)	(0.042)	(0.042)
Region	-0.022	-0.021	-0.020	-0.025
	(0.043)	(0.043)	(0.043)	(0.043)
Employed	0.012	0.006	0.011	0.004
	(0.017)	(0.017)	(0.017)	(0.017)
Unemployed	-0.010	-0.011	-0.009	-0.002
	(0.039)	(0.039)	(0.039)	(0.039)
Retired	-0.030*	-0.029*	-0.029*	-0.031*
	(0.016)	(0.016)	(0.016)	(0.016)
Couple	0.053**	0.051*	0.056**	0.043
	(0.026)	(0.026)	(0.027)	(0.027)
2008	0.030*	0.027	0.028	0.029
	(0.018)	(0.018)	(0.018)	(0.018)
2010	-0.007	-0.013	-0.011	-0.009
	(0.027)	(0.027)	(0.027)	(0.027)
2011	-0.002	-0.009	-0.005	-0.002
	(0.033)	(0.034)	(0.034)	(0.033)
2012	0.005	-0.004	0.001	0.003
	(0.039)	(0.039)	(0.039)	(0.038)
2013	0.069	0.059	0.065	0.066
	(0.044)	(0.044)	(0.044)	(0.044)
2014	0.074	0.063	0.069	0.070
	(0.050)	(0.050)	(0.050)	(0.050)
2015	0.044	0.033	0.039	0.040
	(0.056)	(0.056)	(0.056)	(0.056)
Ln dis. income		0.032***		

		(0.011)		
Ln consumption			0.031**	0.024*
			(0.014)	(0.014)
Ability to raise $2,000 ($3,000 in wave 9+)				
Some sacrifices				-0.042***
				(0.015)
Something drastic				-0.059**
				(0.025)
Couldn't raise				-0.094***
				(0.029)
Prosperity				
Very comfortable				-0.147***
				(0.045)
Reasonably comfortable				-0.197***
				(0.048)
Just getting along				-0.246***
				(0.050)
Poor				-0.238***
				(0.059)
Very poor				-0.307***
				(0.089)
Constant	0.412***	0.061	0.090	0.395*
	(0.142)	(0.182)	(0.209)	(0.217)
Observations	38101	38101	38101	38101

Note: T= 2006, 2008, 2010-2015. The estimates are from an OLS fixed effects regression on risk preferences (standardized) in the financial domain [1-4 scale]. The sample size is slightly smaller than for the main regression results because observations are dropped if household income is negative or if the financial means variables are missing. The base group for ability to raise $2,000 ($3,000 in wave 9+) is "Could easily raise emergency funds". The base group for Prosperity is "Prosperous". Cluster robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: Estimates from Figure 6: Mental health and mood mediation

	(1) Baseline	(2) M H score	(3) Pos/Neg Affect	(4) Life sat.
Improved finances				
0-1 year before	-0.007	-0.007	-0.007	-0.007
	(0.022)	(0.022)	(0.022)	(0.022)
0-3 months after	0.049	0.049	0.049	0.049
	(0.037)	(0.037)	(0.037)	(0.037)
3-6 months after	0.123***	0.123***	0.123***	0.123***
	(0.037)	(0.037)	(0.037)	(0.037)
6-9 months after	0.043	0.043	0.043	0.043
	(0.043)	(0.043)	(0.043)	(0.043)
9-12 months after	0.048	0.048	0.048	0.048
	(0.047)	(0.047)	(0.047)	(0.047)
1-2 years after	0.047**	0.047**	0.047**	0.047**
	(0.024)	(0.024)	(0.024)	(0.024)
2-3+ years after	0.017	0.017	0.017	0.017
	(0.025)	(0.025)	(0.025)	(0.025)
Worsened finances				
0-1 year before	0.053*	0.053*	0.053*	0.053*
	(0.029)	(0.029)	(0.029)	(0.029)
0-3 months after	-0.131***	-0.130***	-0.130***	-0.131***
	(0.050)	(0.050)	(0.050)	(0.050)
3-6 months after	-0.026	-0.025	-0.026	-0.026
	(0.048)	(0.048)	(0.048)	(0.048)
6-9 months after	-0.011	-0.010	-0.010	-0.011
	(0.066)	(0.066)	(0.066)	(0.066)
9-12 months after	-0.017	-0.016	-0.016	-0.016
	(0.050)	(0.050)	(0.050)	(0.050)
1-2 years after	-0.020	-0.020	-0.020	-0.020
	(0.028)	(0.028)	(0.028)	(0.028)
2-3+ years after	-0.096***	-0.096***	-0.096***	-0.096***
	(0.029)	(0.029)	(0.029)	(0.029)
Injury or illness				
0-1 year before	0.024*	0.024*	0.024*	0.024*
	(0.013)	(0.013)	(0.013)	(0.013)
0-3 months after	0.015	0.016	0.016	0.015
	(0.024)	(0.024)	(0.024)	(0.024)
3-6 months after	0.012	0.012	0.013	0.012
	(0.022)	(0.023)	(0.023)	(0.022)
6-9 months after	-0.020	-0.019	-0.019	-0.020
	(0.029)	(0.029)	(0.029)	(0.029)

9-12 months after	0.041	0.041	0.041	0.041
	(0.027)	(0.027)	(0.027)	(0.027)
1-2 years after	0.017	0.017	0.017	0.017
	(0.015)	(0.015)	(0.015)	(0.015)
2-3+ years after	0.004	0.004	0.004	0.004
	(0.018)	(0.018)	(0.018)	(0.018)
Birth first child				
0-1 year before	0.036	0.036	0.036	0.036
	(0.052)	(0.052)	(0.051)	(0.052)
0-3 months after	-0.235**	-0.235**	-0.235**	-0.235**
	(0.094)	(0.094)	(0.094)	(0.094)
3-6 months after	-0.175*	-0.175*	-0.175*	-0.175*
	(0.092)	(0.092)	(0.092)	(0.092)
6-9 months after	0.035	0.034	0.035	0.035
	(0.095)	(0.095)	(0.095)	(0.095)
9-12 months after	-0.089	-0.089	-0.089	-0.089
	(0.089)	(0.089)	(0.089)	(0.089)
1-2 years after	-0.078	-0.078	-0.077	-0.078
	(0.055)	(0.055)	(0.055)	(0.055)
2-3+ years after	-0.066	-0.066	-0.066	-0.066
	(0.051)	(0.051)	(0.051)	(0.051)
Victim of property crime				
0-1 year before	-0.013	-0.013	-0.013	-0.013
	(0.025)	(0.025)	(0.025)	(0.025)
0-3 months after	0.031	0.031	0.031	0.031
	(0.036)	(0.036)	(0.036)	(0.036)
3-6 months after	0.013	0.014	0.014	0.014
	(0.041)	(0.041)	(0.041)	(0.041)
6-9 months after	0.118*	0.118*	0.118*	0.118*
	(0.062)	(0.062)	(0.062)	(0.062)
9-12 months after	-0.020	-0.020	-0.020	-0.020
	(0.053)	(0.053)	(0.053)	(0.053)
1-2 years after	0.017	0.017	0.017	0.017
	(0.025)	(0.025)	(0.025)	(0.025)
2-3+ years after	0.008	0.008	0.008	0.008
	(0.027)	(0.027)	(0.027)	(0.027)
Death of child or spouse				
0-1 year before	0.014	0.015	0.015	0.014
	(0.048)	(0.048)	(0.048)	(0.048)
0-3 months after	-0.116	-0.114	-0.115	-0.116
	(0.079)	(0.079)	(0.079)	(0.079)
3-6 months after	0.059	0.060	0.060	0.059
	(0.070)	(0.070)	(0.070)	(0.070)

6-9 months after	-0.125	-0.124	-0.124	-0.124
	(0.082)	(0.082)	(0.082)	(0.082)
9-12 months after	0.021	0.022	0.022	0.022
	(0.078)	(0.078)	(0.078)	(0.078)
1-2 years after	-0.052	-0.052	-0.052	-0.052
	(0.049)	(0.049)	(0.049)	(0.049)
2-3+ years after	0.023	0.023	0.023	0.023
	(0.048)	(0.048)	(0.048)	(0.048)
Age sq	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
University	-0.006	-0.006	-0.006	-0.006
	(0.072)	(0.072)	(0.072)	(0.072)
Diploma	-0.012	-0.012	-0.012	-0.012
	(0.061)	(0.061)	(0.061)	(0.061)
Student	-0.072*	-0.071*	-0.071*	-0.072*
	(0.042)	(0.042)	(0.042)	(0.042)
Region	-0.019	-0.019	-0.019	-0.019
	(0.043)	(0.043)	(0.043)	(0.043)
Employed	0.016	0.016	0.017	0.016
	(0.017)	(0.017)	(0.017)	(0.017)
Unemployed	-0.008	-0.008	-0.008	-0.008
	(0.039)	(0.039)	(0.039)	(0.039)
Retired	-0.030*	-0.030*	-0.030*	-0.030*
	(0.016)	(0.016)	(0.016)	(0.016)
Couple	0.063**	0.063**	0.063**	0.063**
	(0.026)	(0.026)	(0.026)	(0.026)
2008	0.030	0.030	0.030	0.030
	(0.018)	(0.018)	(0.018)	(0.018)
2010	-0.008	-0.008	-0.008	-0.008
	(0.027)	(0.027)	(0.027)	(0.027)
2011	-0.000	-0.000	-0.000	-0.000
	(0.033)	(0.033)	(0.033)	(0.033)
2012	0.003	0.003	0.003	0.003
	(0.039)	(0.039)	(0.039)	(0.039)
2013	0.066	0.066	0.066	0.066
	(0.044)	(0.044)	(0.044)	(0.044)
2014	0.069	0.069	0.069	0.069
	(0.050)	(0.050)	(0.050)	(0.050)
2015	0.041	0.041	0.041	0.041
	(0.056)	(0.056)	(0.056)	(0.056)
SF36 MH score		0.000		
		(0.000)		
Positive affect			-0.005	

			(0.007)	
Negative affect			-0.002	
			(0.009)	
Life satisfaction				0.001
				(0.006)
Constant	0.387***	0.374***	0.412***	0.388***
	(0.142)	(0.144)	(0.153)	(0.142)
N	38014	38014	38014	38014

Note: T= 2006, 2008, 2010-2015. The estimates are from an OLS fixed effects regression on risk preferences (standardized) in the financial domain [1-4 scale]. The sample size is slightly smaller than for the main regression results because observations are dropped if mental health, positive/negative affect or SWB are missing. Positive affect is the mean response to the following: "Felt calm and peaceful" and "Been a happy person". Negative affect is the mean response to the following: "Been a nervous person", "Felt so down in the dumps nothing could cheer you up" and "Felt down". These are answered on a scale 1 (all of the time) to 6 (none of the time). Life satisfaction is standardized value of "All things considered, how satisfied are you with your life?" – which ranges from 0 (extremely dissatisfied) to 10 (extremely satisfied). Cluster robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D3: Estimates from Figure 5: Regression on life satisfaction

Improved finances		
0-1 year before	-0.575	(0.522)
0-3 months after	0.666	(0.708)
3-6 months after	0.397	(0.794)
6-9 months after	-1.329	(0.882)
9-12 months after	-1.254	(1.110)
1-2 years after	0.739	(0.474)
2-3+ years after	-0.519	(0.375)
Worsened finances		
0-1 year before	0.360	(0.729)
0-3 months after	1.192	(1.490)
3-6 months after	-0.316	(1.040)
6-9 months after	-0.845	(1.954)
9-12 months after	0.442	(1.651)
1-2 years after	-0.343	(0.694)
2-3+ years after	-0.799	(0.514)
Injury or illness		
0-1 year before	-0.551*	(0.328)
0-3 months after	-0.387	(0.631)
3-6 months after	-0.462	(0.579)
6-9 months after	0.281	(0.597)
9-12 months after	-0.264	(0.691)
1-2 years after	-0.600	(0.392)
2-3+ years after	0.261	(0.296)
Birth first child		
0-1 year before	-0.414	(1.101)
0-3 months after	-0.549	(1.767)
3-6 months after	-1.587	(1.192)
6-9 months after	1.832	(2.425)
9-12 months after	-0.342	(1.715)
1-2 years after	-0.212	(1.033)
2-3+ years after	-0.352	(0.446)
Victim of property crime		
0-1 year before	-0.015	(0.466)
0-3 months after	0.809	(0.990)
3-6 months after	-0.518	(0.922)
6-9 months after	1.188	(1.387)
9-12 months after	-0.923	(0.960)
1-2 years after	-0.136	(0.568)
2-3+ years after	-0.230	(0.375)
Death of child or spouse		

0-1 year before	0.601	(1.147)
0-3 months after	7.399**	(3.717)
3-6 months after	1.075	(2.860)
6-9 months after	3.337	(2.147)
9-12 months after	-2.188	(2.230)
1-2 years after	0.593	(1.061)
2-3+ years after	-1.965**	(0.768)
Improved finances × Ln equivalized household consumption		
0-1 year before	0.053	(0.050)
0-3 months after	-0.054	(0.068)
3-6 months after	-0.025	(0.076)
6-9 months after	0.139	(0.086)
9-12 months after	0.128	(0.108)
1-2 years after	-0.068	(0.046)
2-3+ years after	0.054	(0.036)
Worsened finances × Ln equivalized household consumption		
0-1 year before	-0.050	(0.071)
0-3 months after	-0.151	(0.146)
3-6 months after	-0.008	(0.102)
6-9 months after	0.042	(0.192)
9-12 months after	-0.097	(0.163)
1-2 years after	0.025	(0.068)
2-3+ years after	0.071	(0.050)
Injury or illness × Ln equivalized household consumption		
0-1 year before	0.052	(0.032)
0-3 months after	0.024	(0.061)
3-6 months after	0.028	(0.056)
6-9 months after	-0.036	(0.058)
9-12 months after	0.013	(0.067)
1-2 years after	0.053	(0.038)
2-3+ years after	-0.031	(0.029)
Birth first child × Ln equivalized household consumption		
0-1 year before	0.052	(0.107)
0-3 months after	0.074	(0.176)
3-6 months after	0.171	(0.117)
6-9 months after	-0.169	(0.237)
9-12 months after	0.040	(0.167)
1-2 years after	0.010	(0.100)
2-3+ years after	0.023	(0.043)
Victim of property crime × Ln equivalized household consumption		
0-1 year before	0.000	(0.045)
0-3 months after	-0.083	(0.095)
3-6 months after	0.043	(0.090)

6-9 months after	-0.118	(0.133)
9-12 months after	0.089	(0.093)
1-2 years after	0.012	(0.055)
2-3+ years after	0.019	(0.036)
Death of child child or spouse $\times$ *Ln equivalized household consumption*		
0-1 year before	-0.083	(0.112)
0-3 months after	-0.754**	(0.372)
3-6 months after	-0.136	(0.281)
6-9 months after	-0.365*	(0.218)
9-12 months after	0.181	(0.216)
1-2 years after	-0.068	(0.104)
2-3+ years after	0.190**	(0.075)
Age sq	-0.000	(0.000)
University	-0.039	(0.076)
Diploma	0.039	(0.065)
Student	-0.026	(0.045)
Region	-0.060	(0.051)
Employed	0.069***	(0.023)
Unemployed	-0.130***	(0.047)
Retired	0.086***	(0.020)
Couple	0.185***	(0.029)
2008	0.018	(0.018)
2010	0.016	(0.028)
2011	0.062*	(0.033)
2012	0.055	(0.039)
2013	0.064	(0.044)
2014	0.089*	(0.050)
2015	0.102*	(0.056)
Ln consumption	0.013	(0.020)
Constant	-0.237	(0.256)

Note: N= 38,468 (4,810 individuals). T= 2006, 2008, 2010-2015. The estimates are from an OLS fixed effects regression on the standardized value of life satisfaction [0-10 scale]. The sample size is slightly smaller than for the main regression results because observations are dropped if SWB is missing. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D4: Regression results general risk preferences

	(1) OLS	(2) 2SU-OLS	(3) 2SC-OLS
Improved finances			
0-1 year before	0.111	0.068	0.031
	(0.083)	(0.077)	(0.079)
0-1 year after	0.156**	0.123*	0.093
	(0.075)	(0.068)	(0.074)
1-2 years after	0.002	0.032	0.058
	(0.074)	(0.063)	(0.067)
2-3+ years after	0.037	-0.005	-0.043
	(0.034)	(0.032)	(0.038)
Worsened finances			
0-1 year before	0.039	0.139	0.228**
	(0.106)	(0.097)	(0.101)
0-1 year after	0.018	-0.009	-0.034
	(0.112)	(0.105)	(0.112)
1-2 years after	-0.077	-0.079	-0.081
	(0.106)	(0.093)	(0.097)
2-3+ years after	0.060	0.006	-0.042
	(0.040)	(0.040)	(0.048)
Injury or illness			
0-1 year before	-0.047	-0.011	0.022
	(0.048)	(0.045)	(0.048)
0-1 year after	-0.029	-0.008	0.010
	(0.050)	(0.045)	(0.048)
1-2 years after	0.050	0.066	0.079
	(0.051)	(0.049)	(0.052)
2-3+ years after	-0.003	0.026	0.052
	(0.029)	(0.028)	(0.032)
Birth first child			
0-1 year before	-0.440**	-0.403*	-0.369
	(0.200)	(0.213)	(0.242)
0-1 year after	-0.205	-0.273	-0.333
	(0.139)	(0.169)	(0.209)
1-2 years after	-0.452**	-0.497***	-0.538***
	(0.191)	(0.150)	(0.171)
2-3+ years after	0.016	-0.042	-0.093
	(0.050)	(0.051)	(0.067)
Victim of property crime			
0-1 year before	-0.019	-0.069	-0.114
	(0.097)	(0.087)	(0.093)

0-1 year after	0.021	0.033	0.043
	(0.087)	(0.079)	(0.086)
1-2 years after	0.046	0.055	0.062
	(0.078)	(0.073)	(0.083)
2-3+ years after	0.060*	0.057*	0.055
	(0.033)	(0.033)	(0.039)
Death of child or spouse			
0-1 year before	-0.033	0.014	0.056
	(0.151)	(0.142)	(0.153)
0-1 year after	0.095	0.049	0.008
	(0.175)	(0.150)	(0.136)
1-2 years after	-0.163	-0.090	-0.026
	(0.158)	(0.148)	(0.142)
2-3+ years after	-0.032	-0.011	0.008
	(0.068)	(0.061)	(0.067)
Age	-0.007	-0.018**	-0.028***
	(0.008)	(0.007)	(0.008)
Age sq	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Overseas	0.066*	0.097***	0.123***
	(0.035)	(0.032)	(0.034)
University	0.275***	0.039	-0.171**
	(0.033)	(0.047)	(0.073)
Diploma	0.198***	0.068	-0.047
	(0.045)	(0.051)	(0.071)
Student	0.078	0.088	0.097
	(0.124)	(0.114)	(0.119)
Region	0.065	0.090**	0.112**
	(0.044)	(0.046)	(0.057)
Employed	0.077	0.027	-0.018
	(0.057)	(0.053)	(0.057)
Unemployed	0.212*	0.165	0.124
	(0.119)	(0.109)	(0.125)
Retired	-0.180***	-0.165***	-0.151**
	(0.067)	(0.062)	(0.066)
Couple	-0.002	-0.035	-0.063
	(0.034)	(0.034)	(0.040)
Male	0.339***	0.204***	0.083**
	(0.041)	(0.037)	(0.038)
Mother secondary	0.068**	0.016	-0.030
	(0.032)	(0.030)	(0.033)
Father secondary	0.022	0.006	-0.009
	(0.029)	(0.026)	(0.028)

Height	0.004	-0.000	-0.004*
	(0.002)	(0.002)	(0.002)
$\hat{\alpha}_i$		0.529***	1.000
		(0.017)	
Constant	-0.467	0.889**	2.097***
	(0.401)	(0.371)	(0.406)
Observations	4794	4794	4794

Note: The dependent variable is risk preferences in the general domain (standardized), measured on a 0-10 scale and elicited in 2014 only. Coefficients in column 2 are from a multivariate OLS regression. Coefficients in column 3 are from a two-stage unconstrained OLS regression. In the first stage, a linear fixed effects regression is estimated on risk preferences in the financial domain (standardized) measured on a 1-4 scale with the following time varying covariates: age^2, university, diploma, student, region, employed, unemployed, retired, couple, a full set of year dummies and indicators for if a life event occurred -(0-1) year ago, 0-3 months ago, 3-6 months ago, 6-9 months ago, 9-12 months ago, 1-2 years ago or 2-3+ years ago for all of the life events in Table 4. In column 4 a constrained two-stage model is estimated with the restriction ($\hat{\sigma} = 1$). Asymptotic robust standard errors (column 2) and clustered non-parametric bootstrap standard errors in parentheses (columns 3-4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.